



FACULTY OF INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING
DEGREE PROGRAMME IN WIRELESS COMMUNICATIONS ENGINEERING

MASTER'S THESIS

INTER-MICRO-OPERATOR INTERFERENCE PROTECTION IN DYNAMIC TDD SYSTEM

Author	Krishna Joshi
Supervisor	Assoc. Prof. Antti Tölli Dr. Satya Krishna Joshi
Second Examiner	Prof. Markku Juntti

July 2020

Joshi K. (2020) Inter-Micro-Operator Interference Protection in Dynamic TDD System. University of Oulu, Faculty of Information Technology and Electrical Engineering, Degree Programme in Wireless Communications Engineering, 56 p.

ABSTRACT

This thesis considers the problem of weighted sum-rate maximization (WSRM) for a system of micro-operators subject to inter-micro-operator interference constraints with dynamic time division duplexing. The WSRM problem is non-convex and non-deterministic polynomial hard. Furthermore, micro-operators require minimum coordination among themselves making the inter-micro-operator interference management very challenging. In this regard, we propose two decentralized precoder design algorithm based on over-the-air bi-directional signalling strategy. We first propose a precoder design algorithm by considering the equivalent weighted minimum mean-squared error minimization reformulation of the WSRM problem. Later we propose precoder design algorithm by considering the weighted sum mean-squared error reformulation. In both approaches, to reduce the huge signalling requirements in centralized design, we use alternating direction method of multipliers technique, wherein each downlink-operator base station and uplink-operator user determines only the relevant set of transmit precoders by exchanging minimal information among the coordinating base stations and user equipments. To minimize the coordination between the uplink-operator users, we propose interference budget allocation scheme based on reference signal measurements from downlink-operator users. Numerical simulations are provided to compare the performance of proposed algorithms with and without the inter-micro-operator interference constraints.

Keywords: alternating direction method of multipliers, Karush-Kuhn-Tucker, mean-squared error, weighted minimum mean-squared error, weighted sum rate.

TABLE OF CONTENTS

ABSTRACT	
TABLE OF CONTENTS	
FOREWORD	
LIST OF ABBREVIATIONS AND SYMBOLS	
1 INTRODUCTION	9
2 LITERATURE REVIEW AND MATHEMATICAL PRELIMINARIES	12
2.1 MIMO Communication	12
2.2 Time Division Duplex	14
2.3 5G NR Frame Structure	16
2.4 Mathematical Preliminaries	17
2.4.1 Linear signal processing for MIMO Channel	17
2.4.2 KKT Conditions	18
2.4.3 Alternating Direction Method of Multipliers	19
2.4.4 Consensus ADMM for General QCQP	20
3 SYSTEM MODEL AND PROBLEM FORMULATION	22
3.1 System Model	22
3.1.1 Downlink	23
3.1.2 Uplink	24
3.2 Problem Formulation	25
4 ALGORITHM DERIVATION	27
4.1 WMMSE Approach	27
4.1.1 DL Operator Precoder Optimization	28
4.1.2 UL Operator Precoder Optimization	33
4.1.3 Bi-directional Signalling	38
4.2 MSE Approach	40
4.2.1 DL Operator Precoder Optimization	40
4.2.2 UL Operator Precoder Optimization	41
4.2.3 Bi-directional Signalling	41
5 SIMULATION AND NUMERICAL RESULTS	43
6 DISCUSSION	49
7 SUMMARY	51
8 REFERENCES	52

FOREWORD

This thesis was carried out as partial fulfilment for the Master's degree program in Wireless Communications Engineering, University of Oulu, Finland. The research work for the thesis was carried out at Center for Wireless Communication (CWC), University of Oulu, Finland. This thesis work was financially supported by 5G-Enhance project and 6Genesis (6G) Flagship project (grant 318927).

First, I would like to thank my supervisors Assoc. Prof. Antti Tölli and Dr. Satya Krishna Joshi for the constant supervision and guidance throughout the thesis work. I would further like to express my gratitude to Dr. Satya Krishna Joshi for the mentoring and support he provided to me during my Master's studies. Next I thank Prof. Markku Juntti for providing valuable comments and support on my work.

I would like to thank my family for the continuous love, support and encouragement throughout my entire journey. Lastly, I thank all my friends, colleagues and seniors in Oulu for their kind support and motivation.

Oulu, 27th July, 2020

Krishna Joshi

LIST OF ABBREVIATIONS AND SYMBOLS

3GPP	Third generation partnership project
5G	Fifth generation
6G	6 Genesis
ADMM	Alternating directions method of multipliers
BS	Base station
CR	Cognitive radio
CSI	Channel state information
CWC	Center for Wireless Communication
DL	Downlink
DPC	Dirty paper coding
eMBB	Enhanced mobile broadband
FDD	Frequency division duplex
KKT	Karush-Kuhn-Tucker
LMMSE	Linear minimum mean-squared error
MIMO	Multiple-input multiple-output
MISO	Multiple-input single-output
MMSE	Minimum mean squared error
MSE	Mean-squared error
MSEMin	Mean-squared error minimization
MU-MIMO	Multi-user MIMO
NP	Non-deterministic polynomial
NR	New Radio
OFDM	Orthogonal frequency division multiplexing
OTA	Over-the-air
QCQP	Quadratically constrained quadratic programming
SCN	Small cell network
SINR	Signal-to-noise-plus-interference ratio
SISO	Single-input single-output
SNR	Signal-to-noise ratio
STDD	Static time division duplex
SU-MIMO	Single-user MIMO
SVD	Singular value decomposition
TDD	Time division duplex
UE	User equipment
UL	Uplink
WMMSE	Weighted minimum mean-squared error
WMMSEMin	Weighted minimum mean-squared error minimization
WSMSE	Weighted sum mean-squared error
WSR	Weighted sum rate
WSRM	Weighted sum rate maximization
ZF	Zero forcing
μ OP	Micro-operator
\mathbb{C}	Complex number
\mathbb{E}	Expectation

\mathbb{R}	Real number
\mathcal{B}	Set of all BSs
$ \mathcal{B} $	Cardinality of set \mathcal{B}
\mathcal{B}_{DL}	Set of BSs belonging to DL operator
\mathcal{B}_{UL}	Set of BSs belonging to UL operator
B	Total number of BSs
K	Total number of users
b, n	Base station
k, l	User
\mathcal{K}_b	Set of users served by BS b
N	Number of antennas at BS
M	Number of antennas at user
\mathbf{x}_b	Antenna signal vector transmitted by BS b
\mathbf{v}_{bk}	Precoder corresponding to k th user of DL operator BS b
s_{bk}	Information symbol corresponding to k th user of by DL operator BS b
$\bar{\mathbf{x}}_{nl}$	Antenna signal vector transmitted by l th user of UL operator BS n
$\bar{\mathbf{v}}_{nl}$	Precoder corresponding to l th user of UL operator BS n
r_{nl}	Information symbol associated with l th user of UL operator BS n
\mathbf{y}_{bk}	Signal received by k th user of by DL operator BS b
$\mathbf{H}_{b,bk}^{\text{H}}$	Channel matrix between DL operator BS b and k th user of BS b
$\bar{\mathbf{H}}_{nl,bk}$	Interference channel matrix between l th user of UL operator BS n and k th user of DL operator BS b
\mathbf{z}_{bk}	Noise vector at k th user of DL operator BS b
$\bar{\mathbf{z}}_n$	Noise vector at UL operator BS n
σ	Standard deviation of noise
\mathbf{I}	Identity matrix
\mathbf{w}_{bk}	Linear receiver corresponding to k th user of DL operator BS b
\hat{s}_{bk}	Estimated DL information symbol
e_{bk}^{DL}	MSE associated with k th user of DL operator BS b
\mathbf{C}_{bk}	Received signal covariance by k th user of DL operator BS b
$\tilde{e}_{bk}^{\text{DL}}$	MSE corresponding to k th user of DL operator BS b when LMMSE receiver is employed
R_{bk}	DL user rate
\bar{R}_{nl}	UL user rate
γ_{bk}	Interference and noise at DL user
$\bar{\gamma}_{nl}$	Interference and noise at UL user
$\bar{\mathbf{y}}_n$	Signal vector received by UL operator BS n
$\tilde{\mathbf{H}}_{b,n}$	Interference channel matrix between DL BS b and UL BS n
$\bar{\mathbf{w}}_{nl}$	Linear receiver corresponding to l th user of UL operator BS n
\hat{r}_{nl}	Estimated UL information symbol
e_{nl}^{UL}	MSE associated with l th user of UL operator BS n
$\bar{\mathbf{C}}_n$	Received signal covariance by UL operator BS n

$\tilde{e}_{nl}^{\text{UL}}$	MSE corresponding to l th user of UL operator BS n when LMMSE receiver is employed
$\bar{\theta}_n$	Interference threshold for UL operator BS n
θ_{bk}	Interference threshold for k th user of DL operator BS b
μ_{bk}	Arbitrary nonnegative weight assigned to k th user of DL operator BS b
$\bar{\mu}_{nl}$	Arbitrary nonnegative weight assigned to l th user of UL operator BS n
P_b^{\max}	Maximum power of BS b
\bar{P}_{nl}^{\max}	Maximum power of l th user of UL operator BS n
g_{bk}	MMSE weights corresponding to k th user of DL operator BS b
\bar{g}_{nl}	MMSE weights corresponding to l th user of UL operator BS n
\mathbf{a}_{bk}	Auxiliary variable corresponding to k th user in DL-operator BS b defined as $\mathbf{a}_{bk} = \mu_k g_{bk} \mathbf{w}_{bk}^H \mathbf{H}_{b,bk}^H$ and Φ_b
r^i	Primal residual
s^i	dual residual
Φ_b	Backward received covariance matrix corresponding to DL-operator BS b
$\chi_{b,n}$	Auxiliary variable used to represent the interference caused by DL-operator BS b to UL-operator BS n
$u_{b,n}$	Global consensus variable
\mathbf{V}_b	Matrix obtained by stacking all the precoders for users in DL operator BS b
$\boldsymbol{\chi}_b$	Vector obtained by stacking all the auxiliary variables $\chi_{b,n}$ for each DL-operator BS b . i.e., $\boldsymbol{\chi}_b = [\chi_{b,1}, \dots, \chi_{b, \mathcal{B}_{\text{UL}} }]^T$
\mathcal{C}_b	Set of feasible points of the subproblem associated with DL-operator BS b in DL precoder optimization problem
$I(\cdot)$	Indicator function used to represent the feasibility of subproblem associated with DL-operator BS
Ψ_b	Objective function of the DL precoder optimization problem
\mathbf{A}_b	Matrix associated with DL-operator BS b obtained by concatenating \mathbf{a}_{bk} for all $k \in \mathcal{K}_b$
$\lambda_{bn}, \xi_{b,n}, \alpha_b, \bar{\lambda}_{bk}$	Dual variable
ν	Dual variable
L	Partial Lagrangian
L_ρ	Augmented Lagrangian
$\rho, \bar{\rho}$	Penalty parameter
L_0	Standard Lagrangian
β_{bn}	Scaled dual variable
$\mathbf{O}_{b,n}$	Matrix used to denote $\tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n}$
\mathbf{u}_n	Vector obtained by concatenating consensus variables such that $\mathbf{u}_n = [u_{1,n}, u_{2,n}, \dots, u_{ \mathcal{B}_{\text{DL}} ,n}]^T$
$\bar{\mathbf{a}}_{nl}$	Auxiliary variable corresponding to l th user in UL-operator BS n defined as $\bar{\mathbf{a}}_{nl} = \bar{\mu}_{nl} \bar{g}_{nl} \bar{\mathbf{w}}_{nl}^H \mathbf{H}_{n,nl}$

$\bar{\Phi}_{nl}$	Backward received covariance matrix corresponding to l th user in UL-operator BS n
$\mathbf{x}_{bk}^{\text{RS}}$	Reference signal vector transmitted by k th user in DL-operator BS b
\mathbf{p}_{bk}	Pilot sequence corresponding to k th user in DL-operator BS b
$\mathbf{y}_{nl}^{\text{RS}}$	Received reference signal by l th user in UL operator BS n
$P_{nl,bk}^{\text{RS}}$	Received signal power by l th user in UL-operator BS n from k th user in DL-operator BS b
$\bar{\chi}_{nl,bk}$	Auxiliary variable representing the interference from l th user in UL-operator BS n to k th user in DL-operator BS b
$\bar{\mathbf{u}}_{bk}$	Global consensus variable for QCQP problem in UL precoder optimization
$\bar{\mathcal{C}}_{bk}$	Set of feasible points of the subproblem associated with the k th user in DL-operator BS b in UL precoder optimization problem
$\bar{I}(\cdot)$	Indicator function used to represent the feasibility of subproblem associated with l th user in UL-operator BS n
ζ	Auxiliary variable formed such that $\zeta = \bar{\mathbf{v}}^{i+1} - \bar{\beta}^{i+1}$
\mathbf{Q}	Unitary matrix
Λ	Diagonal matrix containing the eigenvalues
$\tilde{\mathbf{u}}$	Global consensus variable formed such that $\tilde{\mathbf{u}} = \mathbf{Q}^H \bar{\mathbf{u}}$
$\varphi(\nu)$	Function of dual variable ν
$\tilde{\zeta}$	Auxiliary variable formed such that $\tilde{\zeta} = \mathbf{Q}^H \zeta$
$\bar{\mathbf{O}}_{bk}$	Matrix used to represent $\bar{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk}$

1 INTRODUCTION

During the last two decades, the mobile communication has evolved rapidly to accomodate the user demands for various wireless services. The fifth generation (5G) new radio (NR) is the state-of-the-art technology in wireless communication. One of the use cases of 5G is to provide enhanced Mobile Broadband (eMBB) with improved performance and increasingly seamless user experience [1]. For different usage scenarios, the requirements for eMBB are different. For example in the hotspot case, the user density is high and it requires very high traffic capacity and user data rates with low mobility. In wide-area coverage case, seamless coverage and medium to high mobility is desired [1].

Thus, in order to provide eMBB to highly dense areas, network densification using locally deployed micro-operators (μ OP) in complement to macro/micro cells is getting a lot of attention [2]. Micro-operator is one of the novel business concepts that provides vertical specific tailored services. Micro-operators complement the existing mobile connectivity by offering context related services and content with the help of emerging 5G technology. Micro-operators promote the deployment of small cell networks (SCN) in specific areas to serve the increasing traffic demand with guaranteed quality of service [3].

Small cells are operator-controlled, low power radio communication equipment that provide wireless communication services within localised areas. Small cells provide cell-splitting gain, and they usually have a range from ten meters to few hundred meters[4]. Small cells provide the benefits of low operational cost and hardware complexity compared to macro cells. Also, SCNs boost network throughput by adopting spatial frequency reuse by deploying large number of cells in a given area so that fewer number of users share time or frequency resources in a cell. With the increase in cell density, users can connect to a closer base station (BS) and thus users suffer smaller path loss [5]. However, the efficient deployment of μ OPs with SCN requires spectrum with quality guarantees.

Conventionally, the radio spectrum is divided into a set of disjoint blocks and are assigned to different operators. But, when a large number of μ OPs are deployed in a geographical area, exclusive allocation of spectrum to each μ OP becomes difficult as spectrum is a scarce resource. Furthermore, μ OP can have different spectrum demand over the time, which may lead to spectrum underutilization. Thus, spectrum sharing between μ OPs operating in the same geographical area is essential to ensure better spectrum utilization [6].

In the literature, several inter-operator spectrum sharing techniques have been studied. Basically, there are two ways to share the spectrum between the operators [7]:

- Orthogonal Sharing: In this type of sharing, a common pool of spectrum is created and operators can share the spectrum with each other; but one spectrum band from the common pool can be used by only one operator at a given time instant.
- Non-orthogonal Sharing: In this type of sharing, multiple operators can transmit on the same spectrum band at the same time. However, the use of same spectrum band by different operators leads to inter-operator interference. Thus interference avoidance schemes in general (scheduling, resource allocation) are required in non-orthogonal sharing to manage inter-operator interferences.

Since, μ OP is a new business concept, spectrum sharing techniques for μ OP is still a topic for further research.

Moreover, the evolution of smart wireless devices has caused an increasing demand for wireless services with asymmetric uplink (UL) and downlink (DL) mobile data traffic [8]. This asymmetric traffic results in poor spectrum utilization in conventional frequency division duplexing (FDD) systems, where UL and DL capacity is determined by fixed frequency allocation [9]. Thus, dynamic time division duplexing (TDD) is becoming an important feature for the modern wireless communication standards, as it is possible to change the UL and DL capacity ratio dynamically according to the traffic need [10]. Even though dynamic TDD improves the spectrum utilization by using same time-slot for both the UL and DL transmission, interference management in dynamic TDD is complicated due to new type of interference scenarios induced in the network [11].

In the literature, most of the works focus on operators either working in DL or UL transmission mode. However, in order to improve the utilization of scarce spectrum resources, the UL and DL resources should be allocated according to the instantaneous UL and DL traffic demand of each cell (unlike in FDD system). In such UL and DL resource scheduling, there is a possibility to assign same time slot for UL/DL transmission in adjacent cells (dynamic TDD); unfortunately this also induces complicated interference scenarios. Managing the interference and acquiring channel state information (CSI) in such a system is very challenging. Also, managing the aggregated UL-to-DL interference is very challenging because of the need of cooperation among all UL users. Spectrum sharing mechanism to manage interference in multi-cell multi-user MISO cognitive radio (CR) networks is provided in [12]. But in case of μ OPs, such spectrum sharing mechanism has not been studied. Thus, a suitable spectrum sharing mechanism to maximize the spectral efficiency of μ OPs is required to guarantee interference protection from other μ OPs operating in the same spectrum band.

The main objective of this thesis is to provide aggregated interference protection between two or more μ OPs operating in the dynamic TDD mode, and simultaneously maximize the overall spectral efficiency of the operators. We consider a special case in which two μ OPs operating in dynamic TDD mode are sharing a same resource element but operating in different UL and DL transmission mode. We propose two iterative algorithms to share spectrum between μ OPs with minimal coordination between them. Since CSI acquisition is challenging and resource consuming, we propose an over-the-air (OTA) pilot aided beamforming technique by estimating the *effective channel* [13].

The organization of rest of the chapters in the thesis is as follows: Chapter 2 discusses the background behind the key areas related to the work in this thesis. This chapter first introduces multiple-input multiple-output (MIMO) communication and summarizes the various works in literature in the field of MIMO communication. Then we provide insights on time division duplex and then discusses the background behind dynamic time division duplex and various interference scenarios and the challenges associated with it. Furthermore, we describe some important features of 5G NR frame structure, which is essential for serving asymmetric traffic with the concept of dynamic TDD. Finally, this chapter provides a brief introduction to the mathematical tools used in this thesis work.

Chapter 3 considers a network with two μ OPs operating in dynamic TDD mode. Here, the design of transmit precoders with weighted sum rate maximization (WSRM) objective in a multi-cell MU-MIMO scenario is considered. The chapter provides the system model used in this thesis and discusses the problem formulation.

Chapter 4 presents the derivation of two fast iterative but sub-optimal algorithm to solve WSRM problem. This chapter discusses the derivation of the algorithms based on alternating optimization technique and alternating direction method of multipliers (ADMM). Here the distributed precoder design techniques, where precoders are designed at each BS and UL user by exchanging some coupling variables between the coordinating BSs and users, is presented. Chapter 5 examines the performance of the proposed algorithms in the considered system using numerical simulations. A discussion on the analyzed results is provided in Chapter 6. Finally, summary of the thesis is given in Chapter 7.

2 LITERATURE REVIEW AND MATHEMATICAL PRELIMINARIES

In this chapter, the background behind the key areas related to the work in this thesis is briefly discussed. This chapter first introduces MIMO communication and summarizes the various works in literature in the field of MIMO communication. Then we provide insights on time division duplex and then discusses the background behind dynamic time division duplex and various interference scenarios and the challenges associated with it. Furthermore, we describe some of the important features of 5G NR frame structure, which is essential for serving asymmetric traffic with the concept of dynamic TDD. Finally, this chapter provides a brief introduction to the mathematical tools used in this thesis work.

2.1 MIMO Communication

The wireless channel in modern mobile communication imposes challenging propagation situations because of its unpredictability and multipath fading. In wireless communication, a transmitted signal usually passes through multiple paths due to reflection from trees, buildings, and other obstacles before it arrives at the receiver. The propagation via multiple path may cause constructive or destructive reception and results in rapid variations of the received signal. Besides the multipath fading, the transmitted signal is also attenuated due to path loss. To overcome the challenges posed by fading wireless channels, using multiple antennas is a viable solution. When only a single antenna is used, the signal propagates in all the directions, where not all directions lead to the user. But with multiple antennas, transmitted signal can be directed towards the users via beamforming and multiple signals can be transmitted in parallel via spatial multiplexing [14]. Generally single-user MIMO (SU-MIMO) offers the benefits of array gain, multiplexing gain, and diversity gain. Array gain refers to the power gain of transmitted signal due to the use of multiple antennas. The multiplexing gain is the improvement in data rate because of the simultaneously transmitted independent data streams in the same frequency band. Diversity gain denotes the improvement in link reliability because of the multiple replicas of transmitted signal available at the receiver [15].

The spectral efficiency of MIMO transmission can be increased if the knowledge of CSI is available at the transmitter [16]. Knowledge of CSI means that the system can adapt to and take advantage of the available spectrum and wireless channel. When CSI is not available, maximum of both of multiplexing gain and diversity gain cannot be achieved, but there is a tradeoff between how much of each of the gains can be achieved as shown in [17]. When CSI is available at both the transmitter and receiver, MIMO channel can be divided into parallel independent single-input single-output (SISO) channels via singular value decomposition (SVD) of the channel matrix. In [18], a capacity achieving strategy using SVD of MIMO channel matrix is proposed.

Generally in cellular system, BSs can be equipped with large number of antennas, but UE can have only few antennas because of the limiting size. In such case, the capacity of SU-MIMO system is limited by the number of antennas at UE. To overcome this limitation and fully leverage the benefits of multiple antennas at BS, multi-user MIMO (MU-MIMO) can be applied. At a given time and frequency subchannel, the BS needs

to decide if it should serve only a single users (with multiplexing) or if it should serve multiple users in different spatial directions. Serving multiple users in different spatial directions by a BS is called MU-MIMO. Basically, MU-MIMO takes advantage of MIMO communications by serving multiple users at the same time. MU-MIMO offers various advantages over conventional point-to-point communication or SU-MIMO [19]:

- Compared to the single user-case where number of parallel data streams is limited by minimum number of transmit and receive antennas, all the receive antennas in case of MU-MIMO is counted. This accounts for decreasing the complexity of the devices by allowing many users with few antennas and limited processing power , instead of one large device with many antennas.
- In MU-MIMO, users that are located in different directions from BS can be selected and thus beamforming can be used to direct each signal towards the intended user without creating much interference to other users.

But, with MU-MIMO, the necessity of CSI being available at the transmitter becomes even more critical to achieve low interference. If CSI is not available, the transmitted signals will mix up and the receivers will only receive a clutter of interfering signals. Since, the communication channels are shared, each transmitter interferes with the received signal of all other receivers. The interference in a MU-MIMO system can be controlled by using proper precoding techniques.

The capacity of a MU-MIMO system is characterized by capacity region, which is given by a set of achievable rates that can be simultaneously achieved with a small joint error probability. Costa introduced the dirty paper coding (DPC) scheme, also known as capacity achieving precoding scheme for MIMO broadcast channel in [20]. DPC is based on successive encoding strategy and it can cancel the interference at transmitter side without extra transmit power requirements. Despite being theoretically optimal, DPC is very challenging to implement in practice when the number of users is high because of the high computational complexity.

Sub-optimal linear beamforming strategies such as zero forcing (ZF) beamforming and minimum mean squared error (MMSE) beamforming provide a reasonable balance between performance and complexity. In [21], it was shown that ZF beamforming can asymptotically achieve the performance of DPC when the number of users is large. However, when number of users is moderate, ZF beamforming suffers from power penalty and it can be applied only when the the number of transmit antennas is greater than or equal to the total number of receiver antennas in the system. In principle,the ZF beamforming tries to null the interference without considering the noise and this may lead to noise amplification. In this regard, another beamforming strategy known as MMSE beamforming has been studied in [22, 23, 24]. In the MMSE beamforming strategy, the beamforming vectors are computed by minimizing the error between the transmitted and received signal. Also, MMSE beamforming provides the advantage of easier implementation and better performance compared to ZF beamforming in terms of spectral efficiency and bit-error rate [22].

In case of multi-cell MIMO system, the performance can be improved by allowing small amount of inter-user interference and jointly optimizing the linear beamformers. Generally, the linear beamformers are optimized with respect to certain performance criteria such as energy efficiency, weighted sum rate (WSR), and weighted sum mean

square error (WSMSE) subject to some practical constraints [10, 25, 26]. In [27, 28, 29] beamformers are designed with the objective to minimize the total transmit power subject to signal-to-interference-plus-noise ratio (SINR) constraints. The weighted sum rate of all users is maximized subject to transmit power constraints in [30, 31, 32]. WSR maximization via mean square error (MSE) minimization was considered in [33]. The main idea in [33] was that the beamformers can be solved iteratively and the power loading can be formulated as a GP by exploiting the uplink-downlink duality. The reformulation of WSRM problem into an weighted minimum mean squared error (WMMSE) problem for MIMO broadcast channel was provided in [34]. In [35], inter-cell interference management via primal decomposition in WSRM with SINR constraints for multiple-input single-output (MISO) system was proposed. In [36, 37] it was shown that dual decomposition with respect to inter-cell interference can be used to decentralize the interference management across adjacent cells. The extension of this approach with alternating direction method of multipliers (ADMM) based decentralized beamformer design was presented in [38].

2.2 Time Division Duplex

Time Division Duplex is an widely used mode of two way communication for most of the low-power, small cell cellular system with little round-trip propagation delays. In TDD, the direction of UL/DL traffic is carried on same carrier frequency but in discrete time intervals. On the other hand, separate frequency channels are allocated for duplex transmission in FDD [39]. In FDD systems, the frequency channel for UL and DL are separated by a guard frequency, where as in TDD, the time slots between UL and DL transmission is separated by a guard time [40]. TDD offers many advantages over FDD such as lower hardware complexity, low power requirements, frequency diversity, and unpaired band allocation. The most important advantage that TDD offers over FDD is that there is channel reciprocity between the links channel characteristics since the same carrier frequency is used for both UL and DL transmission [9]. Also, the use of large antenna arrays is becoming essential for networks to serve multiple users simultaneously and suppress a large number of undesired interference sources. In such scenarios, TDD can be an efficient solution as it helps to avoid problems due to limited pilot resources.

Depending on the allocation of UL/DL resources in the TDD frame, TDD can be categorized into two schemes: static TDD (STDD) and dynamic TDD. In STDD, all DL/UL cell activities needs to be synchronized and UL/DL resource allocation depends on average traffic demand. On the other hand, in dynamic TDD, resources can be freely allocated to either DL or UL depending on the instantaneous traffic demand [41] as shown in Figure 1.

Because of the flexibility to assign resources to DL or UL based on the instantaneous traffic demand, dynamic TDD has been gaining a lot of attention for small cells with asymmetric traffic demand. This overcomes the problem of resource underutilization in STDD with fixed UL/DL configuration and also ensures that a same time resource can be allocated for UL and DL transmission in adjacent cells. Despite the numerous advantages dynamic TDD offers over STDD, it also generates complicated interferences in the network because of the overlapping UL/DL transmissions. The different types of interference scenarios induced in DTDD system are [42]:

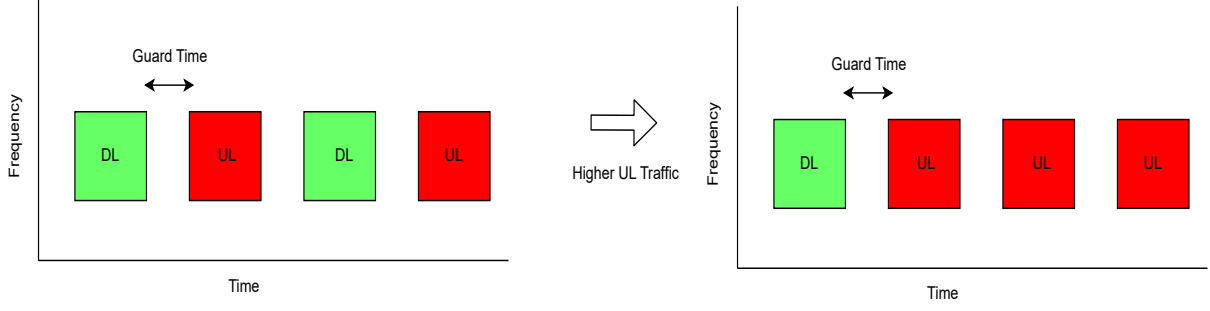


Figure 1. Dynamic allocation of resources in TDD according to instantaneous traffic demand.

- Other-entity: It refers to the interference induced in the network due to different types of equipments. This includes UE-to-BS (UL-to-UL) interference and BS-to-UE (DL-to-DL) interference. These interferences are also found in FDD and STDD mode of operation.
- Same-entity: It refers to the interference induced in the network between same type of equipments. This type of interference arises when DL and UL transmissions in different cells takes place in same time-frequency resource. Same-entity interference includes UE-to-UE (UL-to-DL) and BS-to-BS (DL-to-UL) interference. Same-entity interference is also commonly referred as cross-link or crossed-slot interference.

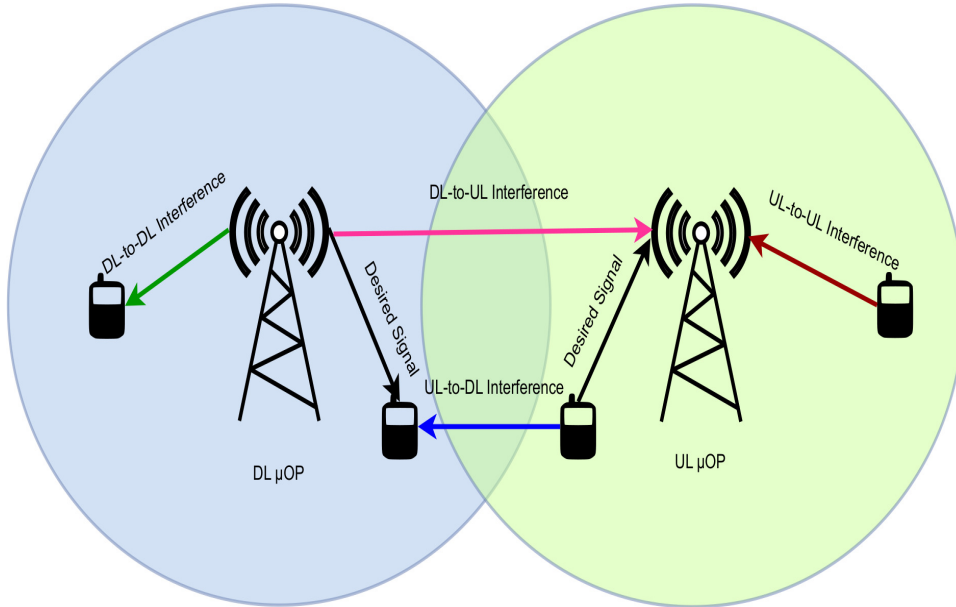


Figure 2. Interference scenarios in DTDD system.

The different kind of interference scenarios induced in a network with two μ OPs operating in different UL/DL configuration in the same time-frequency resource is shown in Figure 2. In small cell deployment where the power of the BS and UE is of same order, UL-to-DL interference is potentially more harmful. Thus, in dynamic TDD system design, interference management is very essential.

In the literature, most of the works in dynamic TDD systems propose time-slot allocation algorithms [10, 25, 26] to manage the cross-slot interference which arises due to simultaneous UL and DL data transmission in adjacent cells. Dynamic time slot allocation using busy burst-signaling is proposed in [10]. The idea in [10] is that when a receiver receives the data, it transmits a busy-burst in the associated multiplexed mini-slot. All other users that sense the busy-burst do not use the same time-slot. In [43] different interference cancellation schemes using cell clustering and power control have been investigated for homogeneous small cell networks. Management of UL-to-DL interference due to users at the cell edge by dividing a cell into inner and outer regions is proposed in [25]. Cross-slot interference management using sector antennas in each cell by coordinating the direction of sector antennas in each cell is presented in [44, 45].

However, for MU-MIMO, CSI at the transmitter is required for beamformer design. By utilizing the property of channel reciprocity in TDD systems, CSI can be acquired via reverse link pilot measurements with OTA bi-directional signaling [13, 46]. By exploiting channel reciprocity, the direct beamformer estimation strategies for dynamic TDD have been provided in [47, 30]. Beamforming techniques with decentralized coordination for multi-cell cellular network is discussed in [12]. Decentralized iterative beamformer design algorithms which manage the UL-to-DL and DL-to-UL interferences in dynamic TDD system are presented in [48, 49, 50].

2.3 5G NR Frame Structure

There is a need for 5G air interfaces to meet the physical layer requirements without restriction on UL/DL slot assignment per cell based on instantaneous traffic demand. For this reason, we present the concept of slot aggregation and mini-slot scheduling features of 5G NR frame structure in this section.

In 5G NR, a single radio frame of 10ms is divided into ten subframes, each with a length of 1ms. Each subframe is further divided into slots with 14 orthogonal frequency division multiplexing (OFDM) symbols, where the duration of a slot depends on different types of subcarrier spacing (numerology). Since the OFDM symbol duration is inversely proportional to the subcarrier spacing, the duration of the slots decreases as the sub carrier spacing increases [51]. The various transmission numerology defined by the third generation partnership project (3GPP) are given in Table 1. Here the numerology $\mu = 0$ represent the subcarrier spacing of 15kHz and it is considered as a baseline in defining the subframe of duration 1ms.

Table 1. Supported transmission numerologies [52]

μ	$\nabla f = 2^\mu 15$ kHz	cyclic prefix
0	15	Normal
1	30	Normal
2	60	Normal, Extended
3	120	Normal
4	240	Normal

An OFDM symbol in a slot in 5G NR frame is considered as a basic UL/DL scheduling interval. A slot can contain all UL symbols, all DL symbols, at least one UL symbol, or at least one DL symbol as shown in Figure 3. These slots can also be concatenated and aggregated to support the asymmetric DL/UL traffic. In addition to slot aggregation, 5G NR also allows mini-slot scheduling, where transmission can be done for a fraction of a slot [51]. The slot aggregation and mini-slot scheduling in 5G NR are very essential features for serving asymmetric traffic and to gain the benefits of dynamic TDD.

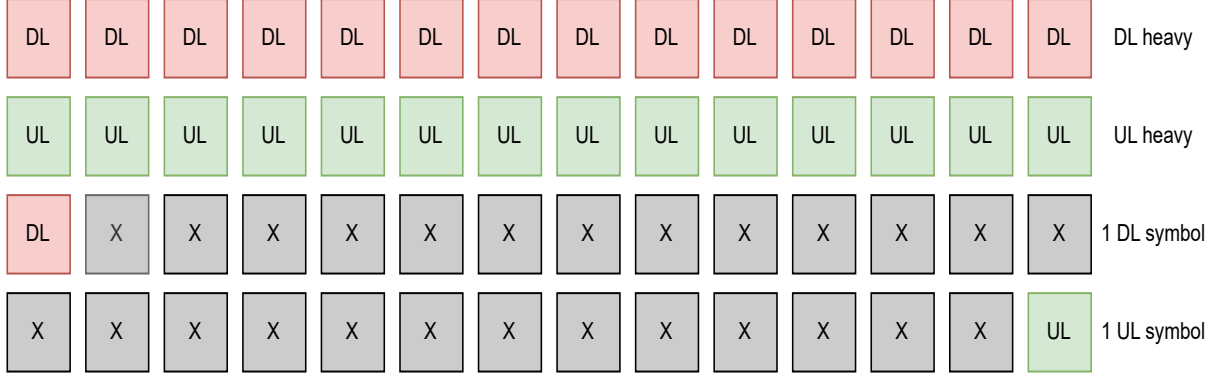


Figure 3. OFDM symbol slots in 5G NR frame.

2.4 Mathematical Preliminaries

This section provides a brief overview of mathematical tools used to obtain the solutions for the problems considered in the thesis. In this section, only the key technical concepts are presented and the rigorous mathematical analysis can be found in the mentioned references.

2.4.1 Linear signal processing for MIMO Channel

In this section we focus on linear transmit-receive processing schemes for MIMO system. The linear processing techniques have low complexity and provide no error feedback problems at the expense of a worse performance. Let us consider the case of a cell in DL transmission with two users. The transmitted vector when using beamvectors $\mathbf{v}_i \in \mathbb{C}^{N \times 1}$ for all $i = 1, 2$ at the transmitter is

$$\mathbf{x} = \sum_{i=1}^2 \mathbf{v}_i s_i, \quad (1)$$

where $s_i \in \mathbb{C}$ is a scalar data symbol with zero mean and normalized such that $\mathbb{E}[|s_i|^2] = 1$. Assuming that the i th receiver employs linear receiver $\mathbf{w}_i \in \mathbb{C}^{M \times 1}$, the estimated data symbol is

$$\hat{s}_i = \mathbf{w}_i^H \mathbf{y}_i, \quad (2)$$

where $\mathbf{y}_i = \mathbf{H}_i \mathbf{x} + \mathbf{z}_i$ is the received antenna vector at the i th user. The matrix $\mathbf{H}_i \in \mathbb{C}^{M \times N}$ is the channel matrix between the transmitter and i th user and \mathbf{z}_i is the complex Gaussian

noise. The mean-squared error corresponding to the estimated data symbol \hat{s}_i with respect to transmitted data symbol s_i is defined as

$$\text{MSE}_i = \mathbb{E}[|\hat{s}_i - s_i|^2]. \quad (3)$$

The MSE is bounded to $0 < \text{MSE} \leq 1$, because of the symbol energy normalization to unity. The upper bound is always attained by setting $\hat{s} = 0$. Unless the noise variance is zero, the lower bound cannot be attained. In practical communication systems, the noise variance cannot be zero. The smaller the MSE in a communication system, the better the system is [53]. However, achieving low MSE requires very large transmit power, which is a highly undesired property of a system. Hence, a communication system has to be designed such that there is a balance between the MSE and available resources (power, spectrum).

The signal-to-interference-plus-noise ratio (SINR) at the receive combiner output (2) is the ratio of desired component and undesired component:

$$\text{SINR}_i = \frac{|\mathbf{w}_i^H \mathbf{H}_i \mathbf{v}_i|^2}{\mathbf{w}_i^H \mathbf{R}_i \mathbf{w}_i}, \quad (4)$$

where $\mathbf{R}_i = \mathbb{E}[\mathbf{y}_i \mathbf{y}_i^H]$. The SINR is bounded by the region $0 < \text{SINR} < \infty$. Unless the channel is noiseless, the upper bound cannot be achieved and the lower bound cannot be achieved unless the desired signal component is zero. For a communication system, the higher the SINR the better the system. The SINR and MSE are related as [53]

$$\text{SINR}_i = \frac{1}{\text{MSE}_i} - 1. \quad (5)$$

A more detailed discussion and analysis on linear processing for MIMO and figures of merit are provided in [53].

2.4.2 KKT Conditions

A convex optimization problem is written in the form [54]:

$$\text{minimize} \quad f_0(\mathbf{x}) \quad (6a)$$

$$\text{subject to} \quad f_i(\mathbf{x}) \leq 0 \quad 1 \leq i \leq m, \quad (6b)$$

$$h_i(\mathbf{x}) = 0 \quad 1 \leq i \leq p, \quad (6c)$$

with the variable $\mathbf{x} \in \mathbb{R}^n$. The functions f_0, \dots, f_m are convex functions, and the functions h_1, \dots, h_p are linear functions. In the Lagrange duality, the objective function is augmented with a weighted sum of constraint functions. Thus, the Lagrangian associated with the problem (6) can be defined as

$$L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = f_0(\mathbf{x}) + \sum_{i=1}^m \lambda_i f_i(\mathbf{x}) + \sum_{i=1}^p \nu_i h_i(\mathbf{x}), \quad (7)$$

where λ_i is the dual variable associated with i th constraint in (6b) and ν_i is the dual variable associated with i th constraint in (6c). By differentiating the Lagrangian over \mathbf{x} , the dual function $g(\boldsymbol{\lambda}, \boldsymbol{\nu})$ can be defined as

$$g(\boldsymbol{\lambda}, \boldsymbol{\nu}) = \inf_{\mathbf{x} \in D} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}), \quad (8)$$

where D is the domain of the of the optimization problem (6). Let \mathbf{x}^* and $(\boldsymbol{\lambda}^*, \boldsymbol{\nu}^*)$ be the primal and dual variables at the optimum. Then the Karush-Kuhn-Tucker (KKT) conditions are stated as:

$$h_i(\mathbf{x}^*) = 0, \quad f_i(\mathbf{x}^*) \leq 0, \quad (9)$$

$$\lambda_i^* \geq 0, \quad (10)$$

$$\nabla_{\mathbf{x}} f_0(\mathbf{x}^*) + \sum_{i=1}^m \lambda_i^* \nabla_{\mathbf{x}} f_i(\mathbf{x}^*) + \sum_{i=1}^p \nu_i^* \nabla_{\mathbf{x}} h_i(\mathbf{x}^*) = 0, \quad (11)$$

$$\lambda_i^* f_i(\mathbf{x}^*) = 0. \quad (12)$$

Optimal solutions can be obtained analytically by using KKT conditions. A more detailed discussion and analysis on KKT conditions can be found in [54, 53]

2.4.3 Alternating Direction Method of Multipliers

ADMM is an iterative method that makes the handling of convex optimization problems easier by breaking them into smaller pieces. ADMM combines the advantages of dual ascent and method of multipliers algorithm and is well suited for distributed implementation with fast converging properties [55]. Let us consider the following convex problem

$$\text{minimize} \quad f(\mathbf{x}) + g(\mathbf{z}) \quad (13a)$$

$$\text{subject to} \quad \mathbf{Ax} + \mathbf{Bz} = \mathbf{c}, \quad (13b)$$

with variables \mathbf{x} and \mathbf{z} , where $f(\mathbf{x}) : \mathbb{C}^n \rightarrow \mathbb{R}$ and $f(\mathbf{z}) : \mathbb{C}^m \rightarrow \mathbb{R}$ are convex functions and $\mathbf{A} \in \mathbb{R}^{l \times n}$, $\mathbf{B} \in \mathbb{R}^{l \times m}$, and $\mathbf{c} \in \mathbb{R}^l$. With the assumption that (13) is solvable and strong duality holds, the augmented Lagrangian (as in method of multipliers) for the ADMM can be written as

$$L_\rho(\mathbf{x}, \mathbf{z}, \boldsymbol{\lambda}) = f(\mathbf{x}) + f(\mathbf{z}) + \boldsymbol{\lambda}^T(\mathbf{Ax} + \mathbf{Bz} - \mathbf{c}) + \frac{\rho}{2} \|\mathbf{Ax} + \mathbf{Bz} - \mathbf{c}\|_2^2, \quad (14)$$

where $\rho > 0$ is the penalty parameter and $\boldsymbol{\lambda}$ is the vector of dual variables associated with the constraint (13b). Each iteration of ADMM consists of three steps, where the primal variables \mathbf{x} and \mathbf{z} are updated alternately in step (15) and (16), respectively, followed by update of dual variables $\boldsymbol{\lambda}$, *i.e.*,

$$\mathbf{x}^{i+1} = \arg \min_{\mathbf{x} \in \mathbb{R}^n} L_\rho(\mathbf{x}, \mathbf{z}^i, \boldsymbol{\lambda}^i), \quad (15)$$

$$\mathbf{z}^{i+1} = \arg \min_{\mathbf{z} \in \mathbb{R}^m} L_\rho(\mathbf{x}^{i+1}, \mathbf{z}, \boldsymbol{\lambda}^i), \quad (16)$$

$$\boldsymbol{\lambda}^{i+1} = \boldsymbol{\lambda}^i + \rho(\mathbf{Ax}^{i+1} + \mathbf{Bz}^{i+1} - \mathbf{c}). \quad (17)$$

The update of primal variables \mathbf{x} and \mathbf{z} follows the same manner as dual decomposition enabling the distributed implementation of ADMM. The sequence of objective values obtained by iterative procedure of the ADMM converges to the optimal value. The penalty term $\frac{\rho}{2} \|\mathbf{Ax} + \mathbf{Bz} - \mathbf{c}\|_2^2$ alleviates the strict convexity of objective in primal variable update. The detailed discussion and analysis of ADMM can be found in [55].

2.4.4 Consensus ADMM for General QCQP

Quadratically constrained quadratic programming (QCQP) is an optimization problem which minimizes a quadratic function subject to quadratic equality and inequality constraints [56]. A QCQP in general form can be written as

$$\text{minimize} \quad \mathbf{x}^H \mathbf{A}_0 \mathbf{x} - 2\Re\{\mathbf{b}_0^H \mathbf{x}\} \quad (18a)$$

$$\text{subject to} \quad \mathbf{x}^H \mathbf{A}_i \mathbf{x} - 2\Re\{\mathbf{b}_i^H \mathbf{x}\} \leq c_i, \quad \forall i = 1, \dots, m, \quad (18b)$$

with variable $\mathbf{x} \in \mathbb{C}^n$, where $\mathbf{A}_i \in \mathbb{C}^{n \times n}$, $\mathbf{b}_i \in \mathbb{C}^n$, and $c_i \in \mathbb{C}$ is a scalar. The general QCQP problem (18) can be transformed into a consensus form as

$$\text{minimize} \quad \mathbf{x}^H \mathbf{A}_0 \mathbf{x} - 2\Re\{\mathbf{b}_0^H \mathbf{x}\} \quad (19a)$$

$$\text{subject to} \quad \mathbf{z}_i^H \mathbf{A}_i \mathbf{z}_i - 2\Re\{\mathbf{b}_i^H \mathbf{z}_i\} \leq c_i, \quad (19b)$$

$$\mathbf{z}_i = \mathbf{x}, \quad \forall i = 1, \dots, m, \quad (19c)$$

with variables \mathbf{x} and $\{\mathbf{z}_i\}_{\forall i}$. Then by following the approach in section 2.4.3, each iteration of corresponding consensus-ADMM algorithm involves following three steps:

$$\mathbf{x} \leftarrow (\mathbf{A}_0 + m\rho\mathbf{I})^{-1} \left(\mathbf{b}_0 + \rho \sum_{i=1}^m (\mathbf{z}_i + \mathbf{u}_i) \right), \quad (20)$$

$$\mathbf{z}_i \leftarrow \arg \min_{\mathbf{z}_i} \|\mathbf{z}_i - \mathbf{x} + \mathbf{u}_i\|^2, \quad \forall i = 1, \dots, m, \quad (21)$$

$$\mathbf{u}_i \leftarrow \mathbf{u}_i + \mathbf{z}_i - \mathbf{x}, \quad \forall i = 1, \dots, m. \quad (22)$$

The update of \mathbf{x} is an unconstrained quadratic minimization problem and update of \mathbf{z}_i is a QCQP with one constraint (QCQP-1) and it can be updated optimally. The efficient update of \mathbf{z}_i for QCQP-1 is discussed below:

Let us define $\boldsymbol{\zeta}_i = \mathbf{x} - \mathbf{u}_i$, then the problem (21) can be denoted as

$$\text{minimize} \quad \|\mathbf{z}_i - \boldsymbol{\zeta}_i\|^2 \quad (23a)$$

$$\text{subject to} \quad \mathbf{z}_i^H \mathbf{A}_i \mathbf{z}_i - 2\Re\{\mathbf{b}_i^H \mathbf{z}_i\} = c_i, \quad (23b)$$

with variable \mathbf{z}_i . For an inequality constraint, if $\boldsymbol{\zeta}_i$ is feasible, then $\boldsymbol{\zeta}_i$ is the solution, else the constraint must be satisfied as equality. If $\mathbf{b}_i = 0$ and \mathbf{A}_i has a rank greater than 1, then there is no closed-form solution for (23), but \mathbf{z}_i can still be updated efficiently. Let $\mathbf{Q}\boldsymbol{\Lambda}\mathbf{Q}^H$ be the eigen-decomposition of \mathbf{A}_i , where \mathbf{Q} is a unitary matrix and $\boldsymbol{\Lambda}$ is diagonal real. We define $\tilde{\mathbf{z}}_i = \mathbf{Q}^H \mathbf{z}_i$ and $\tilde{\boldsymbol{\zeta}} = \mathbf{Q}^H \boldsymbol{\zeta}_i$, then the equivalent problem is

$$\text{minimize} \quad \|\tilde{\mathbf{z}}_i - \tilde{\boldsymbol{\zeta}}_i\|^2 \quad (24a)$$

$$\text{subject to} \quad \tilde{\mathbf{z}}_i^H \boldsymbol{\Lambda} \tilde{\mathbf{z}}_i = c_i, \quad (24b)$$

with variable \mathbf{z}_i . The corresponding Lagrangian is

$$L = \|\tilde{\mathbf{z}}_i - \tilde{\boldsymbol{\zeta}}_i\|^2 + \mu(\tilde{\mathbf{z}}_i^H \boldsymbol{\Lambda} \tilde{\mathbf{z}}_i - c_i), \quad (25)$$

where μ is a Lagrange multiplier. The necessary condition for optimality is $\nabla L = 0$, which upon solving yields the solution for $\tilde{\mathbf{z}}_i$ as

$$\tilde{\mathbf{z}}_i = (\mathbf{I} + \mu\boldsymbol{\Lambda})^{-1} \tilde{\boldsymbol{\zeta}}_i \quad (26)$$

The Lagrange multiplier μ can be found by solving the nonlinear equation (27) via bisection or Newton's method.

$$\sum_{k=1}^n \frac{\lambda_k}{(1 + \mu \lambda_k)^2} |\tilde{\zeta}_{i_k}|^2 = c_i. \quad (27)$$

After finding the value of μ , we can plug it back to (26) to obtain $\tilde{\mathbf{z}}_i$. Then the desired update \mathbf{z}_i is given by $\mathbf{z}_i = \mathbf{Q}\tilde{\mathbf{z}}_i$. A more detailed discussion on consensus ADMM for general QCQP can be found in [57].

3 SYSTEM MODEL AND PROBLEM FORMULATION

In this chapter, we consider a network with two μ OPs operating in dynamic TDD mode. Here, we consider the design of transmit precoders with weighted sum rate maximization objective in a multi-cell MU-MIMO scenario. This chapter provides the system model used in this thesis and discusses the problem formulation.

3.1 System Model

We consider a multi-cell multi-user system operating in dynamic TDD mode with B base stations, belonging to two different micro-operators. We assume that at any time slot, operators share a resource block by operating in different UL/DL transmission modes (i.e., one operator in the DL mode, and another in the UL mode). Without loss of generality, we consider this special case because it captures the difficulty of μ OPs spectrum sharing when both are in synchronous UL or DL mode. We denote the set of BSs that belongs to operator in DL transmission by \mathcal{B}_{DL} , and the set of BSs that belong to operator in UL transmission by \mathcal{B}_{UL} . Hence, the set of BSs in the network is given by $\mathcal{B} = \mathcal{B}_{DL} \cup \mathcal{B}_{UL}$, and we label them with the integer values $b=1, 2, \dots, B$. We denote the set of UEs served by the BS b by \mathcal{K}_b , and we label them with the integer values $k=1, 2, \dots, K_b$. Each BS is equipped with N transmit antennas and each user is equipped with M receive antennas. The overall system model can be illustrated in Figure 4

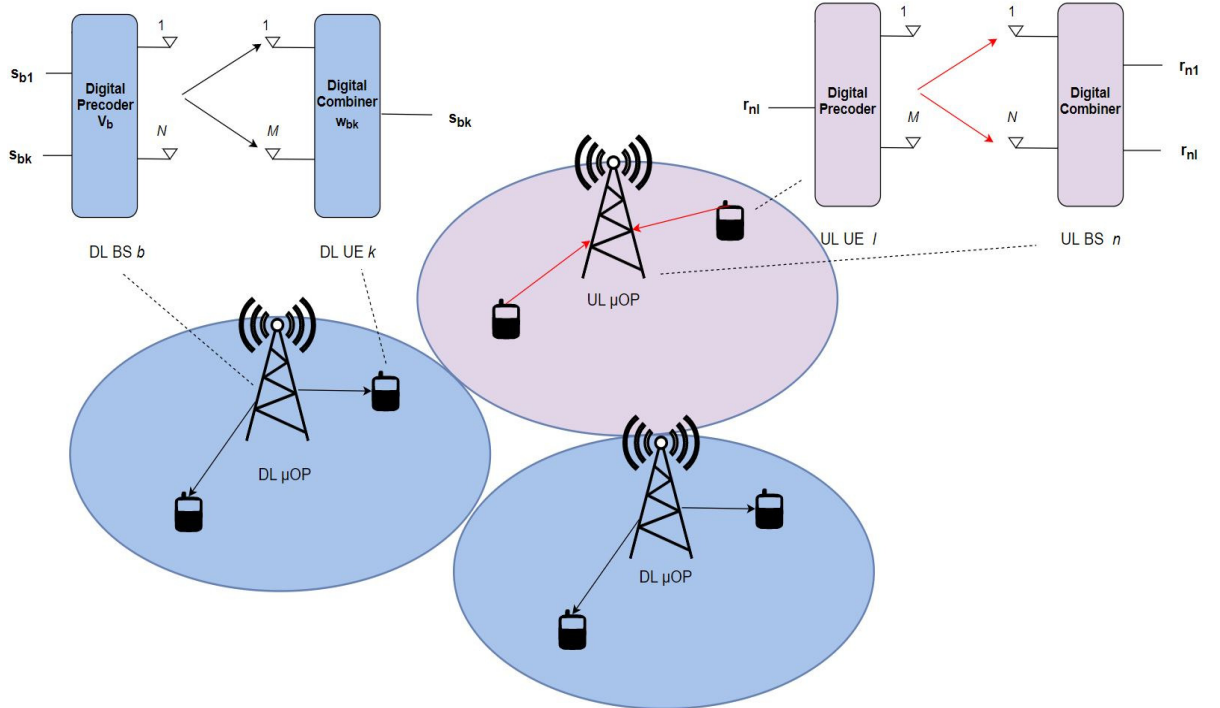


Figure 4. System model.

The antenna signal vector transmitted by b th downlink μ OP BS is given by

$$\mathbf{x}_b = \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk} s_{bk}, \quad (28)$$

where s_{bk} represents information symbol and $\mathbf{v}_{bk} \in \mathbb{C}^{N \times 1}$ represents the precoder associated with k th user of downlink BS b . We assume that s_{bk} is normalized such that $\mathbb{E}[s_{bk} s_{bk}^*] = 1$.

Similarly, the signal transmitted by l th user of uplink μ OP BS n can be expressed as

$$\bar{\mathbf{x}}_{nl} = \bar{\mathbf{v}}_{nl} r_{nl}, \quad (29)$$

where $\bar{\mathbf{v}}_{nl} \in \mathbb{C}^{M \times 1}$ represents the precoder associated with l th user of uplink BS n , and r_{nl} represents the information symbol associated with l th user of uplink BS n . We assume that r_{nl} is normalized such that $\mathbb{E}[r_{nl} r_{nl}^*] = 1$.

3.1.1 Downlink

The signal received by k th user of downlink operator BS b can be expressed as

$$\begin{aligned} \mathbf{y}_{bk} = & \underbrace{\mathbf{H}_{b,bk}^H \mathbf{v}_{bk} s_{bk}}_{\text{Desired Signal}} + \underbrace{\mathbf{H}_{b,bk}^H \sum_{\substack{l \in \mathcal{K}_b \\ l \neq k}} \mathbf{v}_{bl} s_{bl}}_{\text{Intra-cell DL-DL operator interference}} + \underbrace{\sum_{\substack{n \in \mathcal{B}_{DL} \\ n \neq b}} \mathbf{H}_{n,bk}^H \sum_{l \in \mathcal{K}_n} \mathbf{v}_{nl} s_{nl}}_{\text{Inter-cell DL-DL operator interference}} + \\ & \underbrace{\sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} r_{nl}}_{\text{UL-DL operator interference}} + \mathbf{z}_{bk}, \end{aligned} \quad (30)$$

where $\mathbf{H}_{b,bk}^H \in \mathbb{C}^{M \times N}$ denotes the channel vector between b th BS and k th user of BS b , $\bar{\mathbf{H}}_{nl,bk} \in \mathbb{C}^{M \times M}$ represents the interference channel between l th user of uplink operator BS n and k th user of downlink BS b , and \mathbf{z}_{bk} is complex Gaussian noise with variance $\sigma^2 \mathbf{I}$.

Let \mathbf{w}_{bk} be the linear receiver employed by the k th user of downlink BS b . Then the symbol s_{bk} can be estimated as

$$\hat{s}_{bk} = \mathbf{w}_{bk}^H \mathbf{y}_{bk}. \quad (31)$$

The MSE associated with k th user of downlink BS b is given by

$$\begin{aligned} e_{bk}^{\text{DL}} &= \mathbb{E}[(s_{bk} - \hat{s}_{bk})(s_{bk} - \hat{s}_{bk})^H] \\ &= 1 - \mathbf{w}_{bk}^H \mathbf{H}_{b,bk}^H \mathbf{v}_{bk} - (\mathbf{w}_{bk}^H \mathbf{H}_{b,bk}^H \mathbf{v}_{bk})^H + \mathbf{w}_{bk}^H \mathbf{C}_{bk} \mathbf{w}_{bk}, \end{aligned} \quad (32)$$

where \mathbf{C}_{bk} is the received signal covariance and is expressed as

$$\mathbf{C}_{bk} = \left[\sum_{n \in \mathcal{B}_{DL}} \mathbf{H}_{n,bk}^H \left(\sum_{l \in \mathcal{K}_n} \mathbf{v}_{nl} \mathbf{v}_{nl}^H \right) \mathbf{H}_{n,bk} + \sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{H}}_{nl,bk}^H + \sigma^2 \mathbf{I} \right]. \quad (33)$$

We obtain the linear minimum mean-squared-error (LMMSE) receiver associated with k th user of downlink BS b by minimizing (32), for fixed \mathbf{v}_{bk} , and it can be expressed as

$$\mathbf{w}_{bk} = \mathbf{C}_{bk}^{-1} (\mathbf{H}_{b,bk}^H \mathbf{v}_{bk}). \quad (34)$$

When the LMMSE receiver is employed, the corresponding MSE (32) reduces to

$$\tilde{e}_{bk}^{\text{DL}} = 1 - \mathbf{v}_{bk}^H \mathbf{H}_{b,bk} \mathbf{C}_{bk}^{-1} \mathbf{H}_{b,bk}^H \mathbf{v}_{bk}. \quad (35)$$

In this thesis, we assume that Gaussian signaling is used, and the interference from all other UL users and DL BSs is treated as noise. Thus, the rate of k th user of downlink BS b can be expressed as

$$R_{bk} = \log_2(1 + \mathbf{w}_{bk}^H \mathbf{H}_{b,bk}^H \mathbf{v}_{bk} \mathbf{v}_{bk}^H \mathbf{H}_{b,bk} \mathbf{w}_{bk} \gamma_{bk}^{-1}), \quad (36)$$

where γ_{bk} is the interference and is given by

$$\begin{aligned} \gamma_{bk} = \mathbf{w}_{bk}^H & \left[\mathbf{H}_{b,bk}^H \left(\sum_{\substack{l \in \mathcal{K}_b \\ l \neq k}} \mathbf{v}_{bl} \mathbf{v}_{bl}^H \right) \mathbf{H}_{b,bk} + \sum_{\substack{n \in \mathcal{B}_{\text{DL}} \\ n \neq b}} \mathbf{H}_{n,bk}^H \left(\sum_{l \in \mathcal{K}_n} \mathbf{v}_{nl} \mathbf{v}_{nl}^H \right) \mathbf{H}_{n,bk} + \right. \\ & \left. + \sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{H}}_{nl,bk}^H + \sigma^2 \mathbf{I} \right] \mathbf{w}_{bk}. \end{aligned} \quad (37)$$

When the optimal LMMSE receiver is employed, the rate of k th user of downlink BS b can also be expressed as

$$R_{bk} = \log_2(1 + \mathbf{v}_{bk}^H \mathbf{H}_{b,bk} (\mathbf{C}_{bk}^{-1})^H \mathbf{H}_{b,bk}^H \mathbf{v}_{bk} \mathbf{v}_{bk}^H \mathbf{H}_{b,bk} \mathbf{C}_{bk}^{-1} \mathbf{H}_{b,bk}^H \mathbf{v}_{bk} \gamma_{bk}^{-1}). \quad (38)$$

Computing the user rates in practice is difficult because of the requirement of centralized CSI knowledge. Hence, alternating optimization technique is used in practice.

3.1.2 Uplink

Note that the set of BSs \mathcal{B}_{UL} belongs to the micro-operator in the UL transmission mode. The received signal vector by uplink operator BS n is given by

$$\begin{aligned} \bar{\mathbf{y}}_n = & \underbrace{\mathbf{H}_{n,nl} \bar{\mathbf{v}}_{nl} r_{nl}}_{\text{Desired Signal}} + \underbrace{\sum_{\substack{k \in \mathcal{K}_n \\ k \neq l}} \mathbf{H}_{n,nk} \bar{\mathbf{v}}_{nk} r_{nk}}_{\text{Intra-cell UL-UL operator interference}} + \underbrace{\sum_{\substack{b \in \mathcal{B}_{\text{UL}} \\ b \neq n}} \sum_{l \in \mathcal{K}_b} \mathbf{H}_{n,bl} \bar{\mathbf{v}}_{bl} r_{bl}}_{\text{Inter-cell UL-UL operator interference}} + \\ & \underbrace{\sum_{b \in \mathcal{B}_{\text{DL}}} \tilde{\mathbf{H}}_{b,n} \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk} s_{bk}}_{\text{DL-UL operator interference}} + \bar{\mathbf{z}}_n, \end{aligned} \quad (39)$$

where $\mathbf{H}_{n,nl} \in \mathbb{C}^{N \times M}$ represents the channel vector between uplink BS n and l th user of BS n , matrix $\tilde{\mathbf{H}}_{b,n} \in \mathbb{C}^{N \times N}$ represents the interference channel matrix between downlink operator BS b and uplink BS n , and $\bar{\mathbf{z}}_n$ is complex Gaussian noise vector with covariance $\sigma^2 \mathbf{I}$.

Let $\bar{\mathbf{w}}_{nl} \in \mathbb{C}^{N \times 1}$ be the linear combining vector employed by l th user of uplink BS n . Then the symbol r_{nl} can be estimated as

$$\hat{r}_{nl} = \bar{\mathbf{w}}_{nl}^H \bar{\mathbf{y}}_n. \quad (40)$$

The MSE associated with l th user of uplink BS n is given by

$$\begin{aligned} e_{nl}^{\text{UL}} &= \mathbb{E}[(r_{nl} - \hat{r}_{nl})(r_{nl} - \hat{r}_{nl})^H] \\ &= 1 - \bar{\mathbf{v}}_{nl}^H \mathbf{H}_{n,nl}^H \bar{\mathbf{w}}_{nl} - \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{w}}_{nl}^H \mathbf{H}_{n,nl} + \bar{\mathbf{w}}_{nl}^H \bar{\mathbf{C}}_n \bar{\mathbf{w}}_{nl}, \end{aligned} \quad (41)$$

where $\bar{\mathbf{C}}_n$ is the received signal covariance matrix of uplink BS n and is given by

$$\bar{\mathbf{C}}_n = \left[\sum_{b \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_b} \mathbf{H}_{n,bl} \bar{\mathbf{v}}_{nl} \bar{\mathbf{v}}_{nl}^H \mathbf{H}_{n,bl}^H + \sum_{b \in \mathcal{B}_{\text{DL}}} \tilde{\mathbf{H}}_{b,n} \left(\sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk} \mathbf{v}_{bk}^H \right) \tilde{\mathbf{H}}_{b,n}^H + \sigma^2 \mathbf{I} \right]. \quad (42)$$

We obtain the LMMSE receiver associated with l th user of uplink BS n by minimizing (41), for fixed $\bar{\mathbf{v}}_{nl}$, and it can be expressed as

$$\bar{\mathbf{w}}_{nl} = \bar{\mathbf{C}}_n^{-1} (\mathbf{H}_{n,nl} \bar{\mathbf{v}}_{nl}). \quad (43)$$

When the LMMSE receiver is employed, the corresponding MSE (41) reduces to

$$\hat{e}_{nl}^{\text{UL}} = 1 - \bar{\mathbf{v}}_{nl}^H \mathbf{H}_{n,nl}^H \bar{\mathbf{C}}_n^{-1} (\mathbf{H}_{n,nl} \bar{\mathbf{v}}_{nl}). \quad (44)$$

Then the rate of l th user of uplink BS n can be expressed as

$$\bar{R}_{nl} = \log_2(1 + \bar{\mathbf{w}}_{nl}^H \mathbf{H}_{n,nl} \bar{\mathbf{v}}_{nl} \bar{\mathbf{v}}_{nl}^H \mathbf{H}_{n,nl}^H \bar{\mathbf{w}}_{nl} \bar{\gamma}_{nl}^{-1}), \quad (45)$$

where the interference $\bar{\gamma}_{nl}$ is given by

$$\begin{aligned} \bar{\gamma}_{nl} &= \bar{\mathbf{w}}_{nl}^H \left[\sum_{\substack{k \in \mathcal{K}_n \\ k \neq l}} \mathbf{H}_{n,nk} \bar{\mathbf{v}}_{nk} \bar{\mathbf{v}}_{nk}^H \mathbf{H}_{n,nk}^H + \sum_{\substack{b \in \mathcal{B}_{\text{UL}} \\ b \neq n}} \sum_{k \in \mathcal{K}_b} \mathbf{H}_{n,bk} \bar{\mathbf{v}}_{bk} \bar{\mathbf{v}}_{bk}^H \mathbf{H}_{n,bk}^H \right. \\ &\quad \left. + \sum_{b \in \mathcal{B}_{\text{DL}}} \tilde{\mathbf{H}}_{b,n} \left(\sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk} \mathbf{v}_{bk}^H \right) \tilde{\mathbf{H}}_{b,n}^H + \sigma^2 \mathbf{I} \right] \bar{\mathbf{w}}_{nl}. \end{aligned} \quad (46)$$

When the optimal LMMSE receiver is employed, the rate of l th user of uplink BS n can also be expressed as

$$\bar{R}_{nl} = \log_2(1 + \mathbf{v}_{nl}^H \mathbf{H}_{n,nl}^H (\bar{\mathbf{C}}_n^{-1})^H \mathbf{H}_{n,nl} \bar{\mathbf{v}}_{nl} \bar{\mathbf{v}}_{nl}^H \mathbf{H}_{n,nl}^H \bar{\mathbf{C}}_n^{-1} \mathbf{H}_{n,nl} \bar{\mathbf{v}}_{nl} \bar{\gamma}_{nl}^{-1}). \quad (47)$$

3.2 Problem Formulation

Our objective is to provide the aggregated interference protection between two micro-operators operating in the dynamic TDD mode, and simultaneously maximize the overall sum-rate of the operators. We consider an involved scenario where the operators are sharing a same resource element by operating in the different UL and DL transmission mode.

The total interference power generated by \mathcal{B}_{DL} BSs (i.e., all BSs that belong to DL micro-operator) at n th BS of UL micro-operator can be expressed as $\sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk}^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{v}_{bk}$. We assume that this DL-to-UL operator interference is limited by a predefined threshold $\bar{\theta}_n$. Likewise, the total interference power generated by all users that belong to UL micro-operator at k th user of b th BS DL micro-operator can be expressed as $\sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{v}}_{nl}^H \tilde{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \tilde{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl}$. We assume that

this UL-to-DL operator interference is limited by a predefined threshold θ_{bk} . Thus, we have

$$\sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk}^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{v}_{bk} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{\text{UL}}, \quad (48)$$

$$\sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \leq \theta_{bk}, \quad b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b. \quad (49)$$

Let μ_{bk} and $\bar{\mu}_{nl}$ be arbitrary nonnegative weights assigned to k th user of DL BS b and l th user of UL BS n , respectively. Assuming that the power allocation to b th DL BS and l th user of UL BS n are subject to maximum power constraints $\sum_{k \in \mathcal{K}_b} \|\mathbf{v}_{bk}\|_2^2 \leq P_b^{\max}$ and $\|\bar{\mathbf{v}}_{nl}\|_2^2 \leq \bar{P}_{nl}^{\max}$, respectively; the problem of WSRM subject to inter-micro-operator interference constraints can be expressed as

$$\text{maximize} \quad \sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} \mu_{bk} R_{bk} + \sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mu}_{nl} \bar{R}_{nl} \quad (50a)$$

$$\text{subject to} \quad \sum_{k \in \mathcal{K}_b} \|\mathbf{v}_{bk}\|_2^2 \leq P_b^{\max}, \quad b \in \mathcal{B}_{\text{DL}} \quad (50b)$$

$$\|\bar{\mathbf{v}}_{nl}\|_2^2 \leq \bar{P}_{nl}^{\max}, \quad n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n \quad (50c)$$

$$\sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk}^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{v}_{bk} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{\text{UL}}, \quad (50d)$$

$$\sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \leq \theta_{bk}, \quad b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b, \quad (50e)$$

with variables $\{\mathbf{v}_{bk}, \mathbf{w}_{bk}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b}$ and $\{\bar{\mathbf{v}}_{nl}, \bar{\mathbf{w}}_{nl}\}_{n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$.

The precoder design for the WSRM problem (50) is difficult due to the non convex nature of the problem and also impractical due to centralized CSI requirement. In the following chapter, we present two different approaches to solve the non convex WSRM problem based on WMMSEMin and WSMSE minimization.

4 ALGORITHM DERIVATION

In this chapter, we derive two fast-iterative but possibly suboptimal distributed algorithm for NP-hard problem (50). The distributed precoder design can be achieved either by using backhaul to exchange the coupling variables or by using OTA signalling to update respective precoders/combiners. The proposed algorithms are derived based on the alternating optimization technique [58], and is derived in conjunction with ADMM because of its fast converging property [55]. Here we discuss the distributed precoder design techniques where precoders are designed at each DL BS and UL user by exchanging some coupling variables between the coordinating BSs and users.

4.1 WMMSE Approach

By following the approach in [59], we start by writing the WSRM problem (50) equivalently as the minimization of the following utility function:

$$\text{minimize} \quad \sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} \mu_{bk} (g_{bk} e_{bk}^{\text{DL}} - \log(g_{bk})) + \sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mu}_{nl} (\bar{g}_{nl} e_{nl}^{\text{UL}} - \log(\bar{g}_{nl})) \quad (51a)$$

$$\text{subject to} \quad \text{constraints (50b) – (50e)}, \quad (51b)$$

with variables $\{\mathbf{v}_{bk}, \mathbf{w}_{bk}, g_{bk}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b}$ and $\{\bar{\mathbf{v}}_{nl}, \bar{\mathbf{w}}_{nl}, \bar{g}_{nl}\}_{n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$. Problem (50) and (51) are equivalent in a sense that for each choice of precoders, the global optimal point for both the problems is same; we refer the interested reader to [58, 59, 60] for more detail.

In problem (51), the set of UL/DL beamformers $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$, combiners $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$, and the MMSE weights $\{g_{bk}, \bar{g}_{nl}\}$ are optimization variables. Problem (51) is not jointly convex in these three set of variables. However, it is a convex problem in each set of variable $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$, $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$, or $\{g_{bk}, \bar{g}_{nl}\}$ (i.e., by keeping other two set of variables fixed). Thus, we adopt the alternating optimization technique as used in the references [58, 59, 61, 60]. However, deriving an iterative algorithm for problem (51) is not straightforward due to the interference constraints (50d) and (50e), as compared to the works in [58, 59, 60, 61].

For fixed $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$ and $\{g_{bk}, \bar{g}_{nl}\}$, the optimal combiner $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$ is the LMMSE receivers and are given by the expressions (34) and (43). For fixed $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$ and $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$, the update for $\{g_{bk}, \bar{g}_{nl}\}$ is given by

$$g_{bk} = [\tilde{e}_{bk}^{\text{DL}}]^{-1}, \quad \bar{g}_{nl} = [\tilde{e}_{nl}^{\text{UL}}]^{-1}. \quad (52)$$

Problem (51) on variables $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$ is a quadratic optimization problem [54] for fixed $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$ and $\{g_{bk}, \bar{g}_{nl}\}$. Furthermore, this problem decouples across variables $\{\mathbf{v}_{bk}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b}$ and $\{\bar{\mathbf{v}}_{nl}\}_{n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$, since the objective and constraints are separable on these two sets of variables. In the following section we derive an iterative algorithm to find $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$ for problem (51).

4.1.1 DL Operator Precoder Optimization

We first derive an algorithm to find solution for DL precoder $\{\mathbf{v}_{bk}\}$. The problem (51) on variable $\{\mathbf{v}_{bk}\}$ can be expressed as

$$\text{minimize} \quad \sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} (\mathbf{v}_{bk}^H \Phi_b \mathbf{v}_{bk} - 2\Re(\mathbf{a}_{bk} \mathbf{v}_{bk})) \quad (53a)$$

$$\text{subject to} \quad \sum_{k \in \mathcal{K}_b} \|\mathbf{v}_{bk}\|_2^2 \leq P_b^{\max}, \quad b \in \mathcal{B}_{\text{DL}} \quad (53b)$$

$$\sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk}^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{v}_{bk} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{\text{UL}}, \quad (53c)$$

where $\mathbf{a}_{bk} = \mu_k g_{bk} \mathbf{w}_{bk}^H \mathbf{H}_{b,bk}^H$ and Φ_b is

$$\Phi_b = \sum_{n \in \mathcal{B}_{\text{DL}}} \sum_{l \in \mathcal{K}_n} \mu_{nl} (\mathbf{w}_{nl}^H \mathbf{H}_{b,nl}^H)^H g_{nl} (\mathbf{w}_{nl}^H \mathbf{H}_{b,nl}^H) + \sum_{n \in \mathcal{B}_{\text{UL}}} \sum_{l \in \mathcal{K}_n} \bar{\mu}_{nl} (\bar{\mathbf{w}}_{nl}^H \tilde{\mathbf{H}}_{b,n})^H \bar{g}_{nl} (\bar{\mathbf{w}}_{nl}^H \tilde{\mathbf{H}}_{b,n}). \quad (54)$$

Note that in problem (53) the objective function and constraint (53b) is separable in $b \in \mathcal{B}_{\text{DL}}$, one for each DL operator BS. However, constraint (53c) complicates this separation. In order to derive an iterative algorithm by updating $\{\mathbf{v}_{bk}\}_{k \in \mathcal{K}_b}$ on each DL BS, we adopt ADMM method [55] to decompose the problem (53). In this approach, the precoders are designed at each BS by exchanging the coupling variables via backhaul that interconnects all the coordinating BSs. An alternative distributed algorithm based on primal decomposition method has been presented in [12].

To perform a distributed design, we introduce the auxiliary variables, which are inter operator BS-BS interference power from downlink BS b to uplink BS n and is denoted by $\{\chi_{b,n}\}_{n \in \mathcal{B}_{\text{UL}}}$. The resulting problem is expressed as

$$\text{minimize} \quad \sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{k \in \mathcal{K}_b} (\mathbf{v}_{bk}^H \Phi_b \mathbf{v}_{bk} - 2\Re(\mathbf{a}_{bk} \mathbf{v}_{bk})) \quad (55a)$$

$$\text{subject to} \quad \sum_{k \in \mathcal{K}_b} \|\mathbf{v}_{bk}\|_2^2 \leq P_b^{\max}, \quad b \in \mathcal{B}_{\text{DL}}, \quad (55b)$$

$$\text{Tr} \left(\sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk}^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{v}_{bk} \right) \leq \chi_{b,n}, \quad b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}, \quad (55c)$$

$$\chi_{b,n} = u_{b,n}, \quad b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}, \quad (55d)$$

$$\sum_{b \in \mathcal{B}_{\text{DL}}} u_{b,n} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{\text{UL}}, \quad (55e)$$

with variables $\{\mathbf{v}_{bk}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b}$ and $\{\chi_{b,n}, u_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}$. Here, $u_{b,n}$ is the global consensus variable. The constraint (55e) is used to ensure that the sum of the interference from all DL BSs to an UL BS do not violate the interference threshold.

We now express problem (55) more compactly. To do this, let us define the matrix $\mathbf{V}_b = [\mathbf{v}_{b1}, \dots, \mathbf{v}_{bK_b}]$ and $\chi_b = [\chi_{b,1}, \dots, \chi_{b,|\mathcal{B}_{\text{UL}}|}]$, and the following set:

$$\mathcal{C}_b = \left\{ \mathbf{V}_b, \chi_b \left| \begin{array}{l} \text{Tr}(\mathbf{V}_b \mathbf{V}_b^H) \leq P_b^{\max} \\ \text{Tr}(\mathbf{V}_b^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{V}_b) \leq \chi_{b,n}, \quad n \in \mathcal{B}_{\text{UL}} \end{array} \right. \right\} \quad (56)$$

Furthermore, for the sake of brevity, let us define the following functions:

$$I(\{u_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}) = \begin{cases} 0 & \sum_{b \in \mathcal{B}_{\text{DL}}} u_{b,n} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{\text{UL}} \\ \infty & \text{otherwise,} \end{cases} \quad (57)$$

and

$$\Psi_b(\mathbf{V}_b, \boldsymbol{\chi}_b) = \begin{cases} \text{Tr}(\mathbf{V}_b^H \boldsymbol{\Phi}_b \mathbf{V}_b) - 2\Re(\text{Tr}(\mathbf{A}_b \mathbf{V}_b)) & \mathbf{V}_b, \boldsymbol{\chi}_b \in \mathcal{C}_b \\ \infty & \text{otherwise,} \end{cases} \quad (58)$$

where $\mathbf{A}_b = [\mathbf{a}_{b1}, \dots, \mathbf{a}_{bk_b}]^T$.

Using (57) and (58), problem (55) can now be written compactly as

$$\text{minimize} \quad \sum_{b \in \mathcal{B}_{\text{DL}}} \Psi_b(\mathbf{V}_b, \boldsymbol{\chi}_b) + I(\{u_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}) \quad (59a)$$

$$\text{subject to} \quad \chi_{b,n} = u_{b,n}, \quad b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}, \quad (59b)$$

with variables $\{\mathbf{V}_b, \boldsymbol{\chi}_b\}_{b \in \mathcal{B}_{\text{DL}}}$ and $\{u_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}$.

ADMM Algorithm for DL Operator Precoder Optimization

To derive the ADMM algorithm we first form the augmented Lagrangian [55] of problem (59). Let $\{\lambda_{bn}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}$ be the dual variables associated with the equality constraints (59b). Then the augmented Lagrangian can be written as

$$\begin{aligned} L_\rho(\{\mathbf{V}_b, \boldsymbol{\chi}_b\}_{b \in \mathcal{B}_{\text{DL}}}, \{u_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}, \{\lambda_{bn}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}) \\ = \sum_{b \in \mathcal{B}_{\text{DL}}} \Psi_b(\mathbf{V}_b, \boldsymbol{\chi}_b) + I(\{u_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}) \\ + \sum_{b \in \mathcal{B}_{\text{DL}}} \sum_{n \in \mathcal{B}_{\text{UL}}} (\lambda_{bn}(\chi_{b,n} - u_{b,n}) + \rho/2(\chi_{b,n} - u_{b,n})^2), \end{aligned} \quad (60)$$

where $\rho > 0$ is a penalty parameter that adds the quadratic penalty to the standard Lagrangian L_0 for the violation of the equality constraints (59b).

As discussed in 2.4.3, each iteration of ADMM algorithm consists of the following three steps:

$$\mathbf{V}_b^{i+1}, \boldsymbol{\chi}_b^{i+1} = \arg \min_{\mathbf{V}_b, \boldsymbol{\chi}_b \in \mathcal{C}_b} L_\rho(\mathbf{V}_b, \boldsymbol{\chi}_b, \{u_{b,n}^i\}_{n \in \mathcal{B}_{\text{UL}}}, \{\lambda_{bn}^i\}_{n \in \mathcal{B}_{\text{UL}}}), \quad b \in \mathcal{B}_{\text{DL}} \quad (61)$$

$$\{u_{b,n}^{i+1}\} = \arg \min_{\{u_{b,n}\}} L_\rho(\{\mathbf{V}_b^{i+1}, \boldsymbol{\chi}_b^{i+1}\}, \{u_{b,n}\}, \{\lambda_{bn}^i\}), \quad b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}} \quad (62)$$

$$\lambda_{bn}^{i+1} = \lambda_{bn}^i + \rho(\chi_{b,n}^{i+1} - u_{b,n}^{i+1}), \quad b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}} \quad (63)$$

[STEP 1 of ADMM] The update $\mathbf{V}_b^{i+1}, \boldsymbol{\chi}_b^{i+1}$ in (61) is a solution of the following optimization problem:

$$\text{minimize} \quad \Psi_b(\mathbf{V}_b, \boldsymbol{\chi}_b) + \sum_{n \in \mathcal{B}_{\text{UL}}} (\lambda_{bn}^i(\chi_{b,n} - u_{b,n}^i) + \rho/2(\chi_{b,n} - u_{b,n}^i)^2), \quad (64)$$

with variables $\mathbf{V}_b, \boldsymbol{\chi}_b$. Let $\beta_{bn} = (1/\rho)\lambda_{bn}^i$ be the scaled dual variable, then (64) can be written as

$$\text{minimize} \quad \Psi_b(\mathbf{V}_b, \boldsymbol{\chi}_b) + \sum_{n \in \mathcal{B}_{\text{UL}}} (\rho/2)(\chi_{b,n} - u_{b,n}^i + \beta_{bn}^i)^2, \quad (65)$$

with variables $\mathbf{V}_b, \boldsymbol{\chi}_b$.

The optimization problem in (65) for b th DL BS is:

$$\text{minimize} \quad \text{Tr}(\mathbf{V}_b^H \Phi_b \mathbf{V}_b) - 2\mathbb{R}(\text{Tr}(\mathbf{A}_b \mathbf{V}_b)) + \sum_{n \in \mathcal{B}_{UL}} (\rho/2)(\chi_{b,n} - u_{b,n}^i + \beta_{bn}^i)^2 \quad (66a)$$

$$\text{subject to} \quad \text{Tr}(\mathbf{V}_b \mathbf{V}_b^H) \leq P_b^{\max}, \quad (66b)$$

$$\text{Tr}(\mathbf{V}_b^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{V}_b) \leq \chi_{b,n}, \quad n \in \mathcal{B}_{UL}, \quad (66c)$$

where $\{\mathbf{V}_b, \chi_b\}_{b \in \mathcal{B}_{DL}}$ are the optimization variables. To solve problem (66), we adopt dual decomposition. Let $\xi_{b,n}$ be the dual variables associated with the constraint (66c). Then the partial Lagrangian of (66) can be written as

$$\begin{aligned} L(\mathbf{V}_b, \chi_b, d_{b,n}) = & \text{Tr}(\mathbf{V}_b^H \Phi_b \mathbf{V}_b) - 2\mathbb{R}(\text{Tr}(\mathbf{A}_b \mathbf{V}_b)) + \sum_{n \in \mathcal{B}_{UL}} (\rho/2)(\chi_{b,n} - u_{b,n}^i + \beta_{bn}^i)^2 + \\ & + \sum_{n \in \mathcal{B}_{UL}} \xi_{b,n} (\text{Tr}(\mathbf{V}_b^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{V}_b) - \chi_{b,n}). \end{aligned} \quad (67)$$

Given the dual variable $\{\xi_{b,n}\}_{n \in \mathcal{B}_{DL}}$, we can minimize $L(\mathbf{V}_b, \chi_b, \xi_{b,n})$ subject to constraint (66b). Thus the subproblem can now be expressed as

$$\begin{aligned} \text{minimize} \quad & \text{Tr}(\mathbf{V}_b^H \Phi_b \mathbf{V}_b) - 2\mathbb{R}(\text{Tr}(\mathbf{A}_b \mathbf{V}_b)) + \sum_{n \in \mathcal{B}_{UL}} (\rho/2)(\chi_{b,n} - u_{b,n}^i + \beta_{bn}^i)^2 + \\ & + \sum_{n \in \mathcal{B}_{UL}} \xi_{b,n} (\text{Tr}(\mathbf{V}_b^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{V}_b) - \chi_{b,n}) \\ \text{subject to} \quad & \text{Tr}(\mathbf{V}_b \mathbf{V}_b^H) \leq P_b^{\max}, \end{aligned} \quad (68)$$

where $\{\mathbf{V}_b, \chi_b\}$ are the optimization variables.

To make the notations simpler, we denote $\tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n}$ by $\mathbf{O}_{b,n}$. Let α_b be the dual variable associated with the constraint in (68), then the solution for quadratic optimization problem (68) can be obtained by differentiating with respect to each associated primal optimization variables \mathbf{V}_b and χ_b , and setting the gradient to zero.

$$\nabla_{\mathbf{V}_b^*} : \Phi_b \mathbf{V}_b - \mathbf{A}_b^H + \alpha_b \mathbf{V}_b + \sum_{n \in \mathcal{B}_{UL}} \xi_{b,n} \mathbf{O}_{b,n} \mathbf{V}_b = 0, \quad (69)$$

$$\nabla_{\chi_{b,n}} : \rho(\chi_{b,n} - u_{b,n}^i + \beta_{bn}^i) - \xi_{b,n} = 0. \quad (70)$$

Solving (69) for \mathbf{V}_b and (70) for $\chi_{b,n}$ we have

$$\mathbf{V}_b = (\Phi_b + \alpha_b \mathbf{I}_N + \sum_{n \in \mathcal{B}_{UL}} \xi_{b,n} \mathbf{O}_{b,n})^{-1} \mathbf{A}_b^H, \quad (71)$$

$$\chi_{b,n} = \frac{\xi_{b,n}}{\rho} + u_{b,n}^i - \beta_{bn}^i. \quad (72)$$

The dual variable α_b can be found using bisection search to satisfy power constraint $\text{Tr}(\mathbf{V}_b \mathbf{V}_b^H) \leq P_b^{\max}$. Let \mathbf{V}_b^* and $\{\chi_{b,n}^*\}_{n \in \mathcal{B}_{DL}}$ be a solution for (68), then the solution for dual variable $\{\xi_{b,n}\}_{n \in \mathcal{B}_{DL}}$ can be found using projected subgradient method [54].

$$\xi_{b,n}(t+1) = \max \left(\xi_{b,n}(t) + \delta (\text{Tr}((\mathbf{V}_b^*)^H \mathbf{O}_{b,n} \mathbf{V}_b^*) - \chi_{b,n}^*), 0 \right), \quad n \in \mathcal{B}_{DL}. \quad (73)$$

[STEP 2 of ADMM] The update $\{u_{b,n}^{i+1}\}_{b \in \mathcal{B}_{DL}, n \in \mathcal{B}_{UL}}$ in (62) is a solution of the following optimization problem:

$$\begin{aligned} \text{minimize} \quad & I(\{u_{b,n}\}_{b \in \mathcal{B}_{DL}, n \in \mathcal{B}_{UL}}) + \sum_{b \in \mathcal{B}_{DL}} \sum_{n \in \mathcal{B}_{UL}} \left(\lambda_{bn}^i (\chi_{b,n}^{i+1} - u_{b,n}) + \rho/2 (\chi_{b,n}^{i+1} - u_{b,n})^2 \right) \end{aligned} \quad (74)$$

By substituting the expression of $I(\{u_{b,n}\}_{b \in \mathcal{B}_{DL}, n \in \mathcal{B}_{UL}})$

$$\begin{aligned} \text{minimize} \quad & \sum_{b \in \mathcal{B}_{DL}} \sum_{n \in \mathcal{B}_{UL}} (\rho/2) (u_{b,n} - \chi_{b,n}^{i+1} - \beta_{b,n}^i)^2 \\ \text{subject to} \quad & \sum_{b \in \mathcal{B}_{DL}} u_{b,n} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{UL}, \end{aligned} \quad (75)$$

with variables $\{u_{b,n}\}_{b \in \mathcal{B}_{DL}, n \in \mathcal{B}_{UL}}$.

The quadratic optimization problem in (75) is separable for each $n \in \mathcal{B}_{UL}$ and can be expressed as

$$\begin{aligned} \text{minimize} \quad & \sum_{b \in \mathcal{B}_{DL}} (\rho/2) (u_{b,n} - \chi_{b,n}^{i+1} - \beta_{b,n}^i)^2 \\ \text{subject to} \quad & \sum_{b \in \mathcal{B}_{DL}} u_{b,n} \leq \bar{\theta}_n, \end{aligned} \quad (76)$$

with variables $\{u_{b,n}\}_{b \in \mathcal{B}_{DL}}$. Let us assume $\mathbf{u}_n = [u_{1,n}, u_{2,n}, \dots, u_{|\mathcal{B}_{DL}|,n}]^T$ and $\mathbf{x}'_n = \mathbf{x}_n^{i+1} + \boldsymbol{\beta}_n^i$, where $\mathbf{x}_n^{i+1} = [\chi_{1,n}^{i+1}, \chi_{2,n}^{i+1}, \dots, \chi_{|\mathcal{B}_{DL}|,n}^{i+1}]^T$ and $\boldsymbol{\beta}_n^i = [\beta_{1,n}^i, \beta_{2,n}^i, \dots, \beta_{|\mathcal{B}_{DL}|,n}^i]^T$. For the inequality constraint, we check if \mathbf{x}'_n is feasible: if it is feasible then \mathbf{x}'_n is the solution, else the constraint must be satisfied as equality. The solution of the problem (76) when the constraint is equality can be found by solving the Karush-Kuhn-Tucker (KKT) optimality conditions. The solution \mathbf{u}_n can be obtained as

$$\mathbf{u}_n = \mathbf{x}'_n + \frac{\bar{\theta}_n - \mathbf{1}^T}{\|\mathbf{1}\|_2^2}. \quad (77)$$

[STEP 3 of ADMM] The update for the scaled variable β_{bn} can be obtained by solving expression (63) as

$$\beta_{bn}^{i+1} = \beta_{bn}^i + \chi_{b,n}^{i+1} - u_{b,n}^{i+1}, \quad b \in \mathcal{B}_{DL}, n \in \mathcal{B}_{UL}. \quad (78)$$

Finally we summarize the steps of proposed distributed ADMM algorithm for DL precoder optimization problem in Algorithm 1.

Algorithm 1 Distributed ADMM Algorithm for DL Precoder Optimization

1. Initialize: given feasible starting point $\{u_{b,n}^0, \beta_{b,n}^0, \xi_{b,n}\}_{b \in \mathcal{B}_{\text{DL}}, n \in \mathcal{B}_{\text{UL}}}$, and parameter $\rho > 0$. Set iteration indices $i = 0$.
 2. ADMM Iteration
 - (a) Each DL operator BS b updates the local variables $\{\mathbf{V}_b^{i+1}, \boldsymbol{\chi}_b^{i+1}\}$ by solving (71) and (72), respectively. Dual variable $\xi_{b,n}$ is updated using (73).
 - (b) DL operator BSs exchange their updated local variable $\boldsymbol{\chi}_b^{i+1}$ with each other.
 - (c) Each DL operator BS updates $\{u_{b,n}^{i+1}\}_{n \in \mathcal{B}_{\text{UL}}}$ by solving (77) and exchanges with other DL BSs.
 - (d) Each DL operator BS b computes $\{\beta_{bn}\}_{n \in \mathcal{B}_{\text{UL}}}$ by solving (78).
 3. Stopping criterion: if the stopping criterion is satisfied, go to step 4. Otherwise, set $i = i + 1$ and go to step 2.
 4. Return $\{\mathbf{V}_b\}_{b \in \mathcal{B}_{\text{DL}}}$.
-

In step 1 of Algorithm 1, the algorithm is initialized. Step 2 performs the ADMM iterations to compute \mathbf{V}_b in three stages. In the first stage, each DL BS solves the problem (68) with fixed dual variable $\xi_{b,n}$ for local variables $\{\mathbf{V}_b^{i+1}, \boldsymbol{\chi}_b^{i+1}\}$ by solving (71) and (72), respectively. Dual variable $\xi_{b,n}$ is updated using (73). The computed local variable $\boldsymbol{\chi}_b^{i+1}$ is exchanged between all the DL BSs in step 2b. Upon obtaining the coupling variables, the global consensus variable $u_{b,n}$ is updated at each DL BS in step 2c. After the update of global consensus variables, these variables are exchanged between all the DL BSs. In step 2d, the corresponding scaled dual variables are updated at each DL BS. In step 3, the stopping criteria for the ADMM iterations is checked. If the stopping criteria is satisfied, the algorithm returns the DL precoder \mathbf{V}_b , else the ADMM iterations are continued until the stopping criteria is fulfilled.

Standard stopping criteria discussed in [55] is used to stop the ADMM algorithm. Let us define $\boldsymbol{\chi} = [\chi_{1,1}, \dots, \chi_{1,|\mathcal{B}_{\text{UL}}|}, \dots, \chi_{|\mathcal{B}_{\text{DL}}|,1}, \dots, \chi_{|\mathcal{B}_{\text{DL}}|,|\mathcal{B}_{\text{UL}}|}]^T$ and $\mathbf{u} = [u_{1,1}, \dots, u_{1,|\mathcal{B}_{\text{UL}}|}, \dots, u_{|\mathcal{B}_{\text{DL}}|,1}, \dots, u_{|\mathcal{B}_{\text{DL}}|,|\mathcal{B}_{\text{UL}}|}]^T$. Then at the i th ADMM iteration, the primal residual is $\mathbf{r}^i = \mathbf{I}\boldsymbol{\chi}^i - \mathbf{I}\mathbf{u}^i$ and dual residual is $\mathbf{s}^i = -\rho\mathbf{I}^T\mathbf{I}(\mathbf{u}^i - \mathbf{u}^{i-1})$. A reasonable stopping criterion for the ADMM algorithm is that the primal and dual residual must be small *i.e.*,

$$\|\mathbf{r}^i\|_2 \leq \epsilon \quad \text{and} \quad \|\mathbf{s}^i\|_2 \leq \epsilon. \quad (79)$$

The total signalling load at the DL BSs per network level iteration is given by $3(|\mathcal{B}_{\text{DL}}| - 1)|\mathcal{B}_{\text{UL}}|$, since each BS needs variables $\boldsymbol{\chi}_b^{i+1}$, $u_{b,n}^{i+1}$, and β_{bn}^{i+1} from $(|\mathcal{B}_{\text{DL}}| - 1)$ BSs excluding itself. The signalling load per network level iteration in ADMM is higher compared to the signalling load in the solution via primal decomposition method. However, the convergence of ADMM method is much faster than primal decomposition method. This is because of the fact that primal decomposition method employs subgradient method which is slowly converging in nature.

4.1.2 UL Operator Precoder Optimization

We now solve problem (51) for UL precoder $\{\bar{\mathbf{v}}_{nl}\}$, and it can be expressed as

$$\text{minimize} \quad \sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} (\bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\Re(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl})) \quad (80a)$$

$$\text{subject to} \quad \|\bar{\mathbf{v}}_{nl}\|_2^2 \leq \bar{P}_{nl}^{\max}, \quad n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n \quad (80b)$$

$$\sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \leq \theta_{bk}, \quad b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b, \quad (80c)$$

where $\bar{\mathbf{a}}_{nl} = \bar{\mu}_{nl} \bar{g}_{nl} \bar{\mathbf{w}}_{nl}^H \mathbf{H}_{n,nl}$ and $\bar{\Phi}_{nl}$ is

$$\bar{\Phi}_{nl} = \sum_{b \in \mathcal{B}_{UL}} \sum_{k \in \mathcal{K}_b} \bar{\mu}_{bk} (\bar{\mathbf{w}}_{bk}^H \mathbf{H}_{b,nl})^H \bar{g}_{bk} (\bar{\mathbf{w}}_{bk}^H \mathbf{H}_{b,nl}) + \sum_{b \in \mathcal{B}_{DL}} \sum_{k \in \mathcal{K}_b} \mu_{bk} (\mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk})^H g_{bk} (\mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk}). \quad (81)$$

Coordination between all the UL operator users is required to guarantee that the interference thresholds are met at DL operator user. The coordination between the users is very difficult to achieve because of lack of communication links between the users. Thus we propose an algorithm in which we fix the maximum interference that an UL operator user can cause to a DL operator user using signalling scheme as shown in Figure 5.

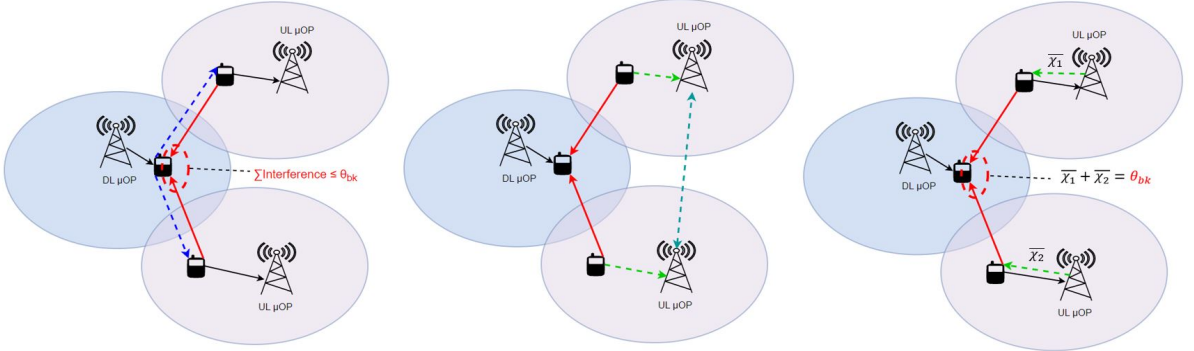


Figure 5. Signalling required to fix new interference thresholds for each UL user based on reference signal measurements.

The proposed algorithm is based on calculation of channel gain at each UL user via reference signal (RS) transmitted from DL user. We assume that DL user transmits an omni-directional reference pilot signal. An omni-directional beam can be generated by activating only a single antenna of the transmitter and setting the weights of other antennas in the precoder as 0. Let \mathbf{p}_{bk} be the pilot sequence associated with k th user in DL BS b . Then the reference signal transmitted by k th user in DL BS b is

$$\mathbf{x}_{bk}^{\text{RS}} = \mathbf{v}_{bk} \mathbf{p}_{bk}. \quad (82)$$

Now the reference signal received by l th user in UL BS n is

$$\mathbf{y}_{nl}^{\text{RS}} = \mathbf{H}_{nl,bk}^H \mathbf{x}_{bk}^{\text{RS}} + \sum_{b \in \mathcal{B}_{DL}} \sum_{\substack{q \in \mathcal{K}_b \\ q \neq k}} \mathbf{H}_{nl,bq}^H \mathbf{x}_{bq}^{\text{RS}} + \bar{\mathbf{z}}_{nl} \quad (83)$$

Then, the received signal power $P_{nl,bk}^{\text{RS}}$ from k th user in DL BS b to l th user in UL BS n can be extracted by multiplying the received signal by the corresponding pilot sequence such that

$$P_{nl,bk}^{\text{RS}} = \|\mathbf{y}_{nl}^{\text{RS}} \mathbf{p}_{bk}^{\text{H}}\|_2^2. \quad (84)$$

Based on the received signal strength from all DL-operator users, new interference thresholds for l th user in UL BS n to the k th user in DL BS b can be computed as

$$\bar{\chi}_{nl,bk} = \frac{P_{nl,bk}^{\text{RS}}}{\left(\sum_{m \in \mathcal{B}_{\text{UL}}} \sum_{q \in \mathcal{K}_m} P_{mq,bk}^{\text{RS}} \right)} \theta_{bk}. \quad (85)$$

Below we summarize the algorithm to fix the UL-to-DL threshold based on the path gain between DL user and UL user.

Algorithm 2 Algorithm to fix the UL-to-DL Interference Threshold

1. Each DL-operator-user transmits omni-directional reference pilot signal $\{\mathbf{x}_{bk}^{\text{RS}}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b}$ with full power by using (82).
 2. Each UL-operator-user computes the received power $\{P_{nl,bk}^{\text{RS}}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b, n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$ from each DL-user by using (84) and reports them to UL-operator-BS.
 3. UL-operator-BSs exchange the reported power $\{P_{nl,bk}^{\text{RS}}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b, n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$ to each other.
 4. Each UL-operator-BS defines new threshold $\{\bar{\chi}_{nl,bk}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b, n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$ for each of its user by using (85).
 5. UL-BS relays back the new thresholds $\{\bar{\chi}_{nl,bk}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b, n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n}$ to the users.
-

In step 1 of Algorithm 2, all DL users transmit an omni-directional reference pilot signal using (82). Each UL user then decodes the received signal from each UL user using the known pilot sequence and then computes the received power using (84) and reports them to the UL BS in step 2. All UL BSs exchange the reported power form each UL user among themselves in step 3. In step 4, each UL BS defines new threshold for its user using (85) and relays it back to the users in step 5.

When the interference from l th user in UL BS n to the k th user in DL BS b is fixed to $\bar{\chi}_{nl,bk}$ based on RS measurements, the optimization problem (80) can be decoupled across l th user in UL BS n as

$$\text{minimize} \quad \bar{\mathbf{v}}_{nl}^{\text{H}} \bar{\mathbf{\Phi}}_{nl} \bar{\mathbf{v}}_{nl} - 2\Re(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl}) \quad (86a)$$

$$\text{subject to} \quad \|\bar{\mathbf{v}}_{nl}\|_2^2 \leq \bar{P}_{nl}^{\max}, \quad (86b)$$

$$\bar{\mathbf{v}}_{nl}^{\text{H}} \bar{\mathbf{H}}_{nl,bk}^{\text{H}} \mathbf{w}_{bk} \mathbf{w}_{bk}^{\text{H}} \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \leq \bar{\chi}_{nl,bk}, \quad b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b, \quad (86c)$$

with variables \mathbf{v}_{nl} .

The quadratically constrained quadratic program (86) can be solved using KKT optimality conditions. But the subgradient method required to update the dual variables

is a slow algorithm. Thus we adopt consensus ADMM to solve the QCQP (86) as discussed in [57]. We first start by writing (86) in consensus form as

$$\text{minimize} \quad \bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\mathbb{R}(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl}) \quad (87a)$$

$$\text{subject to} \quad \|\bar{\mathbf{u}}_{00}\|^2 \leq \bar{P}_{nl}^{\max}, \quad (87b)$$

$$\bar{\mathbf{u}}_{bk}^H \bar{\mathbf{O}}_{bk} \bar{\mathbf{u}}_{bk} \leq \bar{\chi}_{nl,bk}, \quad b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b, \quad (87c)$$

$$\bar{\mathbf{u}}_{bk} = \bar{\mathbf{v}}_{nl}, \quad b \in \mathcal{B}_{DL} \cup \{0\}, k \in \mathcal{K}_b \cup \{0\}, \quad (87d)$$

with variables $\bar{\mathbf{v}}_{nl}$ and $\{\bar{\mathbf{u}}_{bk}\}_{b \in \mathcal{B}_{DL} \cup \{0\}, k \in \mathcal{K}_b \cup \{0\}}$. Here, we denote $\bar{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk}$ by $\bar{\mathbf{O}}_{bk}$ to make the notations simpler.

The problem (87) can be expressed more compactly. To do this, let us define the following set:

$$\bar{\mathcal{C}}_{00} = \left\{ \bar{\mathbf{u}}_{00} \mid \|\bar{\mathbf{u}}_{00}\|^2 \leq \bar{P}_{nl}^{\max} \right\} \quad (88)$$

$$\bar{\mathcal{C}}_{bk} = \left\{ \bar{\mathbf{u}}_{bk} \mid \bar{\mathbf{u}}_{bk}^H \bar{\mathbf{O}}_{bk} \bar{\mathbf{u}}_{bk} \leq \bar{\chi}_{nl,bk} \right\}, \quad b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b, \quad (89)$$

Furthermore, we also define the following function:

$$\bar{I}(\bar{\mathbf{u}}_{bk}) = \begin{cases} 0 & \bar{\mathbf{u}}_{bk} \in \bar{\mathcal{C}}_{bk} \\ \infty & \text{otherwise,} \end{cases} \quad (90)$$

for all $b \in \mathcal{B}_{DL} \cup \{0\}, k \in \mathcal{K}_b \cup \{0\}$.

Then problem (87) in compact form can now be written as

$$\text{minimize} \quad \bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\mathbb{R}(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl}) + \sum_{b \in (\mathcal{B}_{DL} \cup 0)} \sum_{k \in (\mathcal{K}_b \cup 0)} \bar{I}(\bar{\mathbf{u}}_{bk}) \quad (91a)$$

$$\text{subject to} \quad \bar{\mathbf{u}}_{bk} = \bar{\mathbf{v}}_{nl}, \quad b \in (\mathcal{B}_{DL} \cup 0), k \in (\mathcal{K}_b \cup 0) \quad (91b)$$

with variables $\bar{\mathbf{v}}_{nl}$ and $\bar{\mathbf{u}}_{bk}$.

ADMM Algorithm for UL Operator Precoder Optimization

To derive the ADMM algorithm we first form the augmented Lagrangian [55] of problem (91). Let $\{\bar{\lambda}_{bk}\}$ be the dual variables associated with the equality constraints (91b). To make the notations lighter, we define the sets $b \in (\mathcal{B}_{DL} \cup \{0\})$ and $k \in (\mathcal{K}_b \cup \{0\})$. Then the augmented Lagrangian can be written as

$$\begin{aligned} L_{\bar{\rho}}(\bar{\mathbf{v}}_{nl}, \bar{\mathbf{u}}_{bk}, \bar{\lambda}_{bk}) &= \bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\mathbb{R}(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl}) + \sum_b \sum_k \bar{I}(\bar{\mathbf{u}}_{bk}) \\ &\quad + \sum_b \sum_k \left(\bar{\lambda}_{bk}(\bar{\mathbf{u}}_{bk} - \bar{\mathbf{v}}_{nl}) + \bar{\rho}/2 \|\bar{\mathbf{u}}_{bk} - \bar{\mathbf{v}}_{nl}\|^2 \right) \end{aligned} \quad (92)$$

where $\bar{\rho} > 0$ is a penalty parameter that adds the quadratic penalty to the standard Lagrangian L_0 for the violation of the equality constraints (91b).

Each iteration of ADMM algorithm consists of the following three steps:

$$\bar{\mathbf{v}}_{nl}^{i+1} = \arg \min_{\bar{\mathbf{v}}_{nl}} L_{\bar{\rho}}(\bar{\mathbf{v}}_{nl}, \bar{\mathbf{u}}_{bk}^i, \bar{\lambda}_{bk}^i) \quad (93)$$

$$\bar{\mathbf{u}}_{bk}^{i+1} = \arg \min_{\bar{\mathbf{u}}_{bk}} L_{\bar{\rho}}(\bar{\mathbf{v}}_{nl}^{i+1}, \bar{\mathbf{u}}_{bk}, \bar{\lambda}_{bk}^i), \quad \forall b, k \quad (94)$$

$$\bar{\lambda}_{bk}^{i+1} = \bar{\lambda}_{bk}^i + \bar{\rho}(\bar{\mathbf{u}}_{bk}^{i+1} - \bar{\mathbf{v}}_{nl}^{i+1}), \quad \forall b, k \quad (95)$$

[STEP 1 of ADMM] The update $\bar{\mathbf{v}}_{nl}^{i+1}$ in (61) is a solution of the following optimization problem:

$$\text{minimize} \quad \bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\mathbb{R}(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl}) + \sum_b \sum_k \left(\bar{\lambda}_{bk}^i (\bar{\mathbf{u}}_{bk}^i - \bar{\mathbf{v}}_{nl}) + \bar{\rho}/2 \|\bar{\mathbf{u}}_{bk}^i - \bar{\mathbf{v}}_{nl}\|^2 \right) \quad (96)$$

with variables $\bar{\mathbf{v}}_{nl}$. Let $\bar{\beta}_{bk} = (1/\rho) \bar{\lambda}_{bk}$ be the scaled dual variable, then we get

$$\text{minimize} \quad \bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\mathbb{R}(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl}) + \sum_b \sum_k \bar{\rho}/2 \|\bar{\mathbf{u}}_{bk}^i - \bar{\mathbf{v}}_{nl} + \bar{\beta}_{bk}^i\|^2, \quad (97)$$

with variable $\bar{\mathbf{v}}_{nl}$. The solution for (97) can be obtained by differentiating with respect to $(\bar{\mathbf{v}}_{nl}^*)^T$ and setting the gradient to zero. The solution for $\bar{\mathbf{v}}_{nl}$ is then given by:

$$\bar{\mathbf{v}}_{nl}^{i+1} = \left(\bar{\Phi}_{nl} + \sum_b \sum_k \bar{\rho} \mathbf{I} \right)^{-1} \left(\bar{\mathbf{a}}_{nl}^H + \bar{\rho} \sum_b \sum_k (\bar{\mathbf{u}}_{bk}^i + \bar{\beta}_{bk}^i) \right) \quad (98)$$

[STEP 2 of ADMM] The update $\{\bar{\mathbf{u}}_{bk}^{i+1}\}$ in (94) is a solution of the following optimization problem:

$$\text{minimize} \quad \sum_b \sum_k \bar{I}(\bar{\mathbf{u}}_{bk}) + \sum_b \sum_k \left(\bar{\lambda}_{bk}^i (\bar{\mathbf{u}}_{bk} - \bar{\mathbf{v}}_{nl}^{i+1}) + \bar{\rho}/2 \|\bar{\mathbf{u}}_{bk} - \bar{\mathbf{v}}_{nl}^{i+1}\|^2 \right) \quad (99)$$

By substituting the expression of $\bar{I}(\bar{\mathbf{u}}_{bk})$

$$\text{minimize} \quad \sum_b \sum_k (\bar{\rho}/2) \|\bar{\mathbf{u}}_{bk} - \bar{\mathbf{v}}_{nl}^{i+1} + \bar{\beta}_{bk}^i\|^2 \quad (100a)$$

$$\text{subject to} \quad \|\bar{\mathbf{u}}_{00}\|^2 \leq \bar{P}_{nl}^{\max}, \quad (100b)$$

$$\bar{\mathbf{u}}_{bk}^H \bar{\mathbf{O}}_{bk} \bar{\mathbf{u}}_{bk} \leq \bar{\chi}_{nl,bk}, \quad b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b, \quad (100c)$$

with variables $\{\bar{\mathbf{u}}_{bk}\}$.

Problem (100) is separable for each $\{\bar{\mathbf{u}}_{bk}\}$ and can be expressed as:

$$\text{minimize} \quad \|\bar{\mathbf{u}}_{00} - \bar{\mathbf{v}}_{nl}^{i+1} + \bar{\beta}_{00}^i\|^2 \quad (101a)$$

$$\text{subject to} \quad \|\bar{\mathbf{u}}_{00}\|^2 \leq \bar{P}_{nl}^{\max}, \quad (101b)$$

with variable $\bar{\mathbf{u}}_{00}$ and

$$\text{minimize} \quad \|\bar{\mathbf{u}}_{bk} - \bar{\mathbf{v}}_{nl}^{i+1} + \bar{\beta}_{bk}^i\|^2 \quad (102a)$$

$$\text{subject to} \quad \bar{\mathbf{u}}_{bk}^H \bar{\mathbf{O}}_{bk} \bar{\mathbf{u}}_{bk} \leq \bar{\chi}_{nl,bk}, \quad b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b, \quad (102b)$$

with variable $\bar{\mathbf{u}}_{bk}$. For ease of notation, we drop the subscript from (102) and define $\boldsymbol{\zeta} = \bar{\mathbf{v}}^{i+1} - \bar{\boldsymbol{\beta}}^{i+1}$ and denote the sub-problem as

$$\text{minimize} \quad \|\bar{\mathbf{u}} - \boldsymbol{\zeta}\|^2 \quad (103a)$$

$$\text{subject to} \quad \bar{\mathbf{u}}^H \bar{\mathbf{O}} \bar{\mathbf{u}} \leq \bar{\chi}, \quad (103b)$$

with variable $\bar{\mathbf{u}}$. For an inequality constraint, we check whether $\boldsymbol{\zeta}$ is feasible: if it is feasible then $\boldsymbol{\zeta}$ is the solution, else the constraint must be satisfied as equality. Thus (103) can be expressed as:

$$\text{minimize} \quad \|\bar{\mathbf{u}} - \boldsymbol{\zeta}\|^2 \quad (104a)$$

$$\text{subject to} \quad \bar{\mathbf{u}}^H \bar{\mathbf{O}} \bar{\mathbf{u}} = \bar{\chi}, \quad (104b)$$

with variable $\bar{\mathbf{u}}$. Let $\mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^H$ be the eigen-decomposition of $\bar{\mathbf{O}}$, where $\mathbf{\Lambda}$ is diagonal real matrix and \mathbf{Q} is unitary matrix. We define $\tilde{\mathbf{u}} = \mathbf{Q}^H \bar{\mathbf{u}}$, $\tilde{\boldsymbol{\zeta}} = \mathbf{Q}^H \boldsymbol{\zeta}$, then the problem is equivalent to

$$\begin{aligned} & \text{minimize} \quad \|\tilde{\mathbf{u}} - \tilde{\boldsymbol{\zeta}}\|^2 \\ & \text{subject to} \quad \tilde{\mathbf{u}}^H \mathbf{\Lambda} \tilde{\mathbf{u}} = \bar{\chi}, \end{aligned}$$

with variable $\tilde{\mathbf{u}}$. The solution for $\tilde{\mathbf{u}}$ can be found as

$$\tilde{\mathbf{u}} = (\mathbf{I} + \nu \mathbf{\Lambda})^{-1} \tilde{\boldsymbol{\zeta}}, \quad (105)$$

where ν is the Lagrange multiplier. The Lagrange multiplier ν can be numerically computed by using Bisection method to satisfy $\varphi(\nu) = 0$, where $\varphi(\nu)$ is defined as [57]:

$$\varphi(\nu) = \sum_{m=1}^M \frac{\lambda_m}{(1 + \nu \lambda_m)^2} |\tilde{\zeta}_m|^2 - \bar{\chi}, \quad (106)$$

Thus the solution for $\bar{\mathbf{u}}$ is obtained as

$$\bar{\mathbf{u}} = \mathbf{Q} \tilde{\mathbf{u}}. \quad (107)$$

The process to solve step 2 of ADMM algorithm for UL precoder optimization problem is presented in Algorithm 3.

Algorithm 3 Algorithm to solve step 2 of ADMM

1. Given feasible starting points $\{\zeta_{bk}\}_{b \in (\mathcal{B}_{DL} \cup \{0\}), k \in (\mathcal{K}_b \cup \{0\})}$.
 2. Compute eigen-decomposition of $\{\bar{\mathbf{O}}_{bk}\}_{b \in (\mathcal{B}_{DL} \cup \{0\}), k \in (\mathcal{K}_b \cup \{0\})}$ and form $\tilde{\boldsymbol{\zeta}}_{bk} = \mathbf{Q}^H \boldsymbol{\zeta}_{bk}$.
 3. Each UL-operator-user computes $\{\tilde{\mathbf{u}}_{bk}\}_{b \in (\mathcal{B}_{DL} \cup \{0\}), k \in (\mathcal{K}_b \cup \{0\})}$ using (105) until bisection search satisfies $\varphi(\nu) = 0$.
 4. Each UL-operator-user computes $\{\bar{\mathbf{u}}_{bk}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$ by using (107).
 5. Return: $\{\bar{\mathbf{u}}_{bk}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$.
-

Given the feasible starting point, UL user computes the eigen-decomposition of $\bar{\mathbf{O}}_{bk}$ and forms $\tilde{\boldsymbol{\zeta}}_{bk}$. In step 3, UL user computes $\tilde{\mathbf{u}}_{bk}$ for all using (105) until bisection search satisfies $\varphi(\nu) = 0$. In step 4, using $\tilde{\mathbf{u}}_{bk}$, UL user computes \mathbf{u}_{bk} by solving (107). Step 5 returns the computed \mathbf{u}_{bk} .

[STEP 3 of ADMM] Expression (95), in the scaled variable can be expressed as

$$\bar{\beta}_{bk}^{i+1} = \bar{\beta}_{bk}^i + \bar{\mathbf{u}}_{bk}^{i+1} - \bar{\mathbf{v}}_{nl}^{i+1}, \quad \forall b, k. \quad (108)$$

The ADMM algorithm to optimize the UL precoder is summarized in Algorithm 4.

Algorithm 4 ADMM Algorithm for UL Precoder Optimization

1. Initialize: given feasible starting points $\{\mathbf{u}_{bk}^0, \beta_{bk}^0\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$, and parameter $\bar{\rho} > 0$. Set iteration indices $i = 0$.
 2. ADMM iteration
 - (a) UL user computes precoder $\bar{\mathbf{v}}_{nl}^{i+1}$ by solving (98).
 - (b) UL user updates $\{\bar{\mathbf{u}}_{bk}^{i+1}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$ is updated using algorithm 3.
 - (c) UL user computes dual variable $\{\beta_{bk}^{i+1}\}_{b \in (\mathcal{B}_{DL} \cup \{0\}), k \in (\mathcal{K}_b \cup \{0\})}$ by solving (108).
 3. Stopping criterion: if the stopping criterion is satisfied, go to step 4. Otherwise set $i = i + 1$ and go to step 2.
 4. Return $\bar{\mathbf{v}}_{nl}$.
-

In step 1, the algorithm is initialized. Step 2 carries out the ADMM operation in 3 stages. In step 2a, UL user computes the precoder $\bar{\mathbf{v}}_{nl}^{i+1}$ by solving (98). Step 2b calls algorithm 3 to update $\bar{\mathbf{u}}_{bk}^{i+1}$. In step 2c, the dual variables β_{bk}^{i+1} are updated using (108). Stopping criteria for ADMM iterations is checked in step 3. If the stopping criteria is satisfied, precoder $\bar{\mathbf{v}}_{nl}$ is returned in step 5, else the ADMM iterations are continued.

4.1.3 Bi-directional Signalling

In Algorithm 5, we have employed forward and backward over-the-air signalling strategy. When the transmitters are sending training sequence (*i.e.*, in DL cells, BS are transmitting and in the UL cells, user are transmitting), we refer it as forward direction. When the receivers are sending training sequence (*i.e.*, in DL cells, users are transmitting and in UL cells BSs are transmitting), we refer it as backward direction. In the forward signalling (step 2 of Algorithm 5), transmit precoders are used to precode the pilot sequence. Then by using the received signal and pilot knowledge, MMSE receiver and weight matrices are calculated. In the backward signalling (step 3 of Algorithm 5), over-the-air signalling is done in two stages to enable to extract all parameters required to estimate precoders by using Algorithm 1 and Algorithm 4.

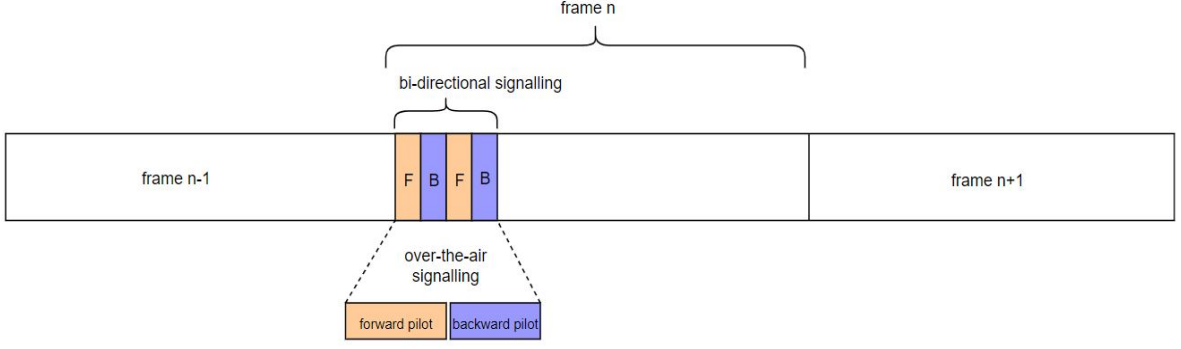


Figure 6. Bi-directional signalling.

Algorithm 5 allows a fully distributed coordinated computation of precoders and combiners without full CSI exchange over a backhaul. This beamformer training signalling strategy can be practically implemented in a 5G NR frame structure by the use of mini-slot scheduling as illustrated in Figure 6. We assume that the micro-operators use the same signalling structure for the training phase, so that the beamformer optimization phase would reflect the real interference scenario during the transmission phase.

Algorithm 5 Bi-directional Signaling for beamformer design

1. All UL operator BSs compute the interference budget for all UL users using Algorithm 2.
 2. Initialize: Initialize feasible UL and DL precoder $\{\mathbf{v}_{bk}^0\}$ and $\{\bar{\mathbf{v}}_{nl}^0\}$, respectively. Set iteration indices $i = 1$.
 3. Forward pilot signaling: each DL-BS and UL-user transmit pilot signals using precoders $\{\mathbf{v}_{bk}^{i-1}\}$ and $\{\bar{\mathbf{v}}_{nl}^{i-1}\}$. Then each DL-user and UL-BS locally computes:
 - MMSE receivers $\{\mathbf{w}_{bk}^i\}$ and $\{\bar{\mathbf{w}}_{nl}^i\}$.
 - Weight matrices $\{g_{bk}^i\}$ and $\{\bar{g}_{nl}^i\}$.
 4. Backward pilot signaling: each DL-user and UL-BS transmits two backward pilot signals. In the first backward pilot signal, signal is precoded with MMSE receivers $\{\mathbf{w}_{bk}^i\}$ and $\{\bar{\mathbf{w}}_{nl}^i\}$. In the second pilot signal, the signal is precoded with $\{g_{bk}^i \mathbf{w}_{bk}^i\}$ and $\{\bar{g}_{nl}^i \bar{\mathbf{w}}_{nl}^i\}$.
 - each DL-BS computes precoder $\{\mathbf{v}_{bk}^i\}$ by using algorithm 1.
 - each UL-user computes precoder $\{\bar{\mathbf{v}}_{nl}^i\}$ by using algorithm 4
 5. STOP, if the stopping criterion (until convergence) is satisfied. Otherwise, set $i = i + 1$ and go to step 3.
-

4.2 MSE Approach

In this section, we use weighted sum MSE minimization problem to optimize the precoders $\{\mathbf{v}_{bk}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$ and $\{\bar{\mathbf{v}}_{nl}\}_{n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n}$. The proposed algorithm can be taken as an alternative to WSRM problem. The weighted sum MSE minimization problem shows only a minor deviation in terms of sum rate performance as compared to the WSRM problem, meanwhile providing fairness across all the users.

We start by writing the the following weighted sum MSE minimization problem:

$$\text{minimize} \quad \sum_{b \in \mathcal{B}_{DL}} \sum_{k \in \mathcal{K}_b} \mu_{bk} e_{bk}^{\text{DL}} + \sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} \bar{\mu}_{nl} e_{nl}^{\text{UL}} \quad (109a)$$

$$\text{subject to} \quad \text{constraints (50b) - (50e)}, \quad (109b)$$

with variables $\{\mathbf{v}_{bk}, \mathbf{w}_{bk}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$ and $\{\bar{\mathbf{v}}_{nl}, \bar{\mathbf{w}}_{nl}\}_{n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n}$.

Similar to the WMMSEMin problem (51), we adopt the alternating optimization technique, where precoders are optimized for fixed combiners and vice versa in an iterative manner.

For fixed $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$, the optimal combiner $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$ is the LMMSE receivers and are given by the expressions (34) and (43). Problem (109) on variables $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$ is a quadratic optimization problem [54] for fixed $\{\mathbf{w}_{bk}, \bar{\mathbf{w}}_{nl}\}$. Furthermore, this problem decouples across variables $\{\mathbf{v}_{bk}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$ and $\{\bar{\mathbf{v}}_{nl}\}_{n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n}$, since the objective and constraints are separable on these two set of variables. In the following section we derive an iterative algorithm to find $\{\mathbf{v}_{bk}, \bar{\mathbf{v}}_{nl}\}$ for problem (109).

4.2.1 DL Operator Precoder Optimization

We first derive an algorithm to find solution for DL precoder $\{\mathbf{v}_{bk}\}$. The problem (109) on variable $\{\mathbf{v}_{bk}\}$ can be expressed as

$$\text{minimize} \quad \sum_{b \in \mathcal{B}_{DL}} \sum_{k \in \mathcal{K}_b} (\mathbf{v}_{bk}^H \boldsymbol{\Phi}_b \mathbf{v}_{bk} - 2\Re(\mathbf{a}_{bk} \mathbf{v}_{bk})) \quad (110a)$$

$$\text{subject to} \quad \sum_{k \in \mathcal{K}_b} \|\mathbf{v}_{bk}\|_2^2 \leq P_b^{\max}, \quad b \in \mathcal{B}_{DL} \quad (110b)$$

$$\sum_{b \in \mathcal{B}_{DL}} \sum_{k \in \mathcal{K}_b} \mathbf{v}_{bk}^H \tilde{\mathbf{H}}_{b,n}^H \left(\sum_{l \in \mathcal{K}_n} \bar{\mathbf{w}}_{nl} \bar{\mathbf{w}}_{nl}^H \right) \tilde{\mathbf{H}}_{b,n} \mathbf{v}_{bk} \leq \bar{\theta}_n, \quad n \in \mathcal{B}_{UL}, \quad (110c)$$

where $\mathbf{a}_{bk} = \mu_k \mathbf{w}_{bk}^H \mathbf{H}_{b,bk}^H$ and $\boldsymbol{\Phi}_b$ is

$$\boldsymbol{\Phi}_b = \sum_{n \in \mathcal{B}_{DL}} \sum_{l \in \mathcal{K}_n} \mu_{nl} (\mathbf{w}_{nl}^H \mathbf{H}_{b,nl}^H)^H (\mathbf{w}_{nl}^H \mathbf{H}_{b,nl}^H) + \sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} \bar{\mu}_{nl} (\bar{\mathbf{w}}_{nl}^H \tilde{\mathbf{H}}_{b,n}^H)^H (\bar{\mathbf{w}}_{nl}^H \tilde{\mathbf{H}}_{b,n}). \quad (111)$$

Note that the problem (110) is similar to the problem (53) with the only difference being the received backward covariance matrix $\boldsymbol{\Phi}_b$ and \mathbf{a}_{bk} . Hence the solution for problem (110) follows the same approach as in WMMSEMin problem (53). The acquisition of the backward covariance matrix $\boldsymbol{\Phi}_b$ and \mathbf{a}_{bk} is discussed in Algorithm 6.

4.2.2 UL Operator Precoder Optimization

We now solve problem (109) for UL precoder $\{\bar{\mathbf{v}}_{nl}\}$, and it can be expressed as

$$\text{minimize} \quad \sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} (\bar{\mathbf{v}}_{nl}^H \bar{\Phi}_{nl} \bar{\mathbf{v}}_{nl} - 2\Re(\bar{\mathbf{a}}_{nl} \bar{\mathbf{v}}_{nl})) \quad (112a)$$

$$\text{subject to} \quad \|\bar{\mathbf{v}}_{nl}\|_2^2 \leq \bar{P}_{nl}^{\max}, \quad n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n \quad (112b)$$

$$\sum_{n \in \mathcal{B}_{UL}} \sum_{l \in \mathcal{K}_n} \bar{\mathbf{v}}_{nl}^H \bar{\mathbf{H}}_{nl,bk}^H \mathbf{w}_{bk} \mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk} \bar{\mathbf{v}}_{nl} \leq \theta_{bk}, \quad b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b, \quad (112c)$$

where $\bar{\mathbf{a}}_{nl} = \bar{\mu}_{nl} \bar{\mathbf{w}}_{nl}^H \mathbf{H}_{n,nl}$ and $\bar{\Phi}_{nl}$ is

$$\bar{\Phi}_{nl} = \sum_{b \in \mathcal{B}_{UL}} \sum_{k \in \mathcal{K}_b} \bar{\mu}_{bk} (\bar{\mathbf{w}}_{bk}^H \mathbf{H}_{b,nl})^H (\bar{\mathbf{w}}_{bk}^H \mathbf{H}_{b,nl}) + \sum_{b \in \mathcal{B}_{DL}} \sum_{k \in \mathcal{K}_b} \mu_{bk} (\mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk})^H (\mathbf{w}_{bk}^H \bar{\mathbf{H}}_{nl,bk}). \quad (113)$$

Here the problem (112) is also similar to the UL precoder optimization problem (80) with only difference being the backward covariance matrix $\bar{\Phi}_{nl}$ and $\bar{\mathbf{a}}_{nl}$. Hence the solution for problem (112) follows the same approach as in WMMSEMin problem (80). The acquisition of $\bar{\Phi}_{nl}$ and $\bar{\mathbf{a}}_{nl}$ is also discussed in algorithm 6.

4.2.3 Bi-directional Signalling

Algorithm 6 Bi-directional Signaling for MSE beamformer design

1. All UL operator BSs compute the interference budget for all UL users using Algorithm 2.
 2. Initialize: Initialize feasible UL and DL precoder $\{\mathbf{v}_{bk}^0\}$ and $\{\bar{\mathbf{v}}_{nl}^0\}$, respectively. Set iteration indices $i = 1$.
 3. Fixing UL-to-DL Interference Threshold: The interference thresholds are fixed by using Algorithm 2.
 4. Forward pilot signaling: each DL-BS and UL-user transmit pilot signals using precoders $\{\mathbf{v}_{bk}^{i-1}\}$ and $\{\bar{\mathbf{v}}_{nl}^{i-1}\}$. Then each DL-user and UL-BS locally computes:
 - MMSE receivers $\{\mathbf{w}_{bk}^i\}$ and $\{\bar{\mathbf{w}}_{nl}^i\}$.
 5. Backward pilot signaling: each DL-user and UL-BS transmits a backward pilot signal precoded with MMSE receivers $\{\mathbf{w}_{bk}^i\}$ and $\{\bar{\mathbf{w}}_{nl}^i\}$.
 - each DL-BS computes precoder $\{\mathbf{v}_{bk}^i\}$ by using algorithm 1.
 - each UL-user computes precoder $\{\bar{\mathbf{v}}_{nl}^i\}$ by using algorithm 4.
 6. STOP, if the stopping criterion (until convergence) is satisfied. Otherwise, set $i = i + 1$ and go to step 4.
-

In Algorithm 6, all the steps are similar to Algorithm 5 except step 4. Here in step 4, we use only one backward signal to compute $\{\Phi_b, \bar{\Phi}_{nl}\}$ and $\{\mathbf{a}_{bk}, \bar{\mathbf{a}}_{nl}\}$ instead of two backward signals as in Algorithm 5. In the backward signalling (step 4 of Algorithm 6), receive beamformers are used to precode pilot sequence to enable to extract all parameters required to estimate precoders by using Algorithm 1 and Algorithm 4.

5 SIMULATION AND NUMERICAL RESULTS

In this section, we illustrate the performance of proposed Algorithms 5 and 6 using setup as shown in Figure 7. The system consists of two micro-operators, one operating in DL transmission mode another operating in UL transmission mode with three cells each. We

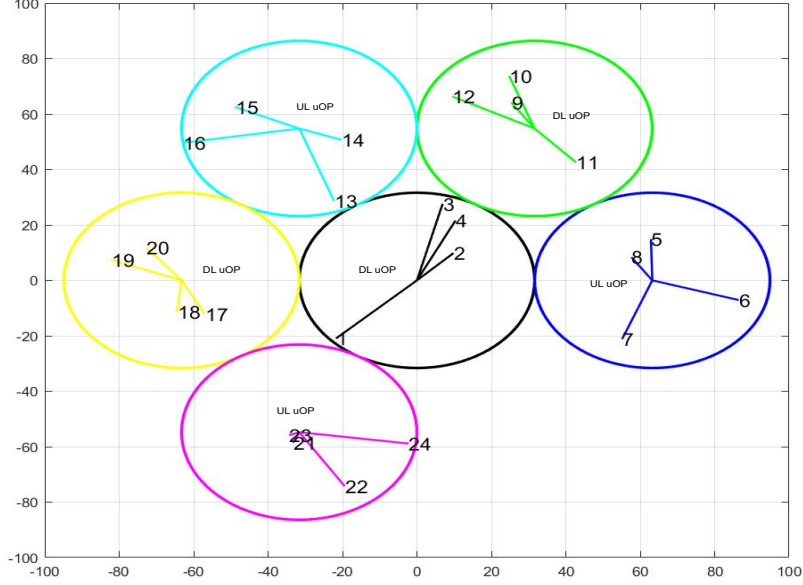


Figure 7. User distribution model.

assume that each BS is equipped with $N=16$ antennas and each cell has $\{K_b = 4\}_{b \in \mathcal{B}}$ users each equipped with $M = 4$ antennas. All the users associated with each BS are distributed randomly as shown in Figure 7. All the BSs and users communicate via single data stream and all the priority weights are assumed to be 1 ($\{\mu_{bk} = 1\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b}$ and $\{\bar{\mu}_{nl} = 1\}_{n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n}$). We assume an exponential path loss model, where the channel matrix between b th BS and k th user of BS b is modeled as

$$\mathbf{H}_{b,bk} = \left(\frac{d_{b,bk}}{d_0} \right)^{-\eta/2} \mathbf{J}_{b,bk}, \quad (114)$$

where $d_{b,bk}$ is the distance between b th BS and k th user of BS b , d_0 is the far field reference distance, η is the path loss exponent and $\mathbf{J}_{b,bk} \in \mathbb{C}^{M \times N}$ is arbitrarily chosen from the distribution $\mathcal{CN}(0, \mathbf{I})$ to generate a frequency-flat fading channel. Interference channels are generated using same model as in (114).

We define path loss at cell edge as $PL = 10 \log_{10}(R/d_0)^{-\eta}$, where R is the radius of the cell. In the simulations, we set $d_0 = 1$, $\eta = 2$, and $PL = 30$ dB. The cell radius R is fixed throughout the simulations such that $R = d_0 \times 10^{(\frac{PL}{10\eta})}$. The maximum transmit power for each BS is fixed at $\{P_b^{\max} = 10\text{dB}\}_{b \in \mathcal{B}}$. The maximum transmit power of UL user is selected such that the maximum sum power of all UL users in a cell is equal to P_b^{\max} , i.e., $\{P_{bl}^{\max} = P_b^{\max}/K_b\}_{b \in \mathcal{B}_{UL}, l \in \mathcal{K}_b}$. For fixed transmit power, the received power at the receiver is $P_{rx} = P_b^{\max} - PL$. Thus for a given signal-to-noise ratio (SNR) operating

point, the noise power N_0 is given by $N_0 = P_{rx} - SNR$. is equal to the power constraint of BS such that $\{P_{nl}^{\max} = P_n^{\max}/K_n\}_{n \in \mathcal{B}_{UL}, l \in \mathcal{K}_n}$.

Figure 8 shows the convergence of the ADMM algorithm for DL operator when we implement the standard stopping criteria [55] for ADMM iterations. Here the ADMM penalty parameter ρ is set to 10 and the error ϵ is fixed to 10^{-2} . The objective value of the auxiliary problem (55) of the ADMM algorithm when number of ADMM iterations are fixed to 10 is shown by the magenta line. The red line shows the objective value of the auxiliary problem (55) when the standard stopping criteria is implemented. The markers 'circle' represent the start of ADMM for a new point. Results show that when the standard stopping criteria is implemented, fewer number of ADMM iterations is required as the ADMM algorithm progresses.

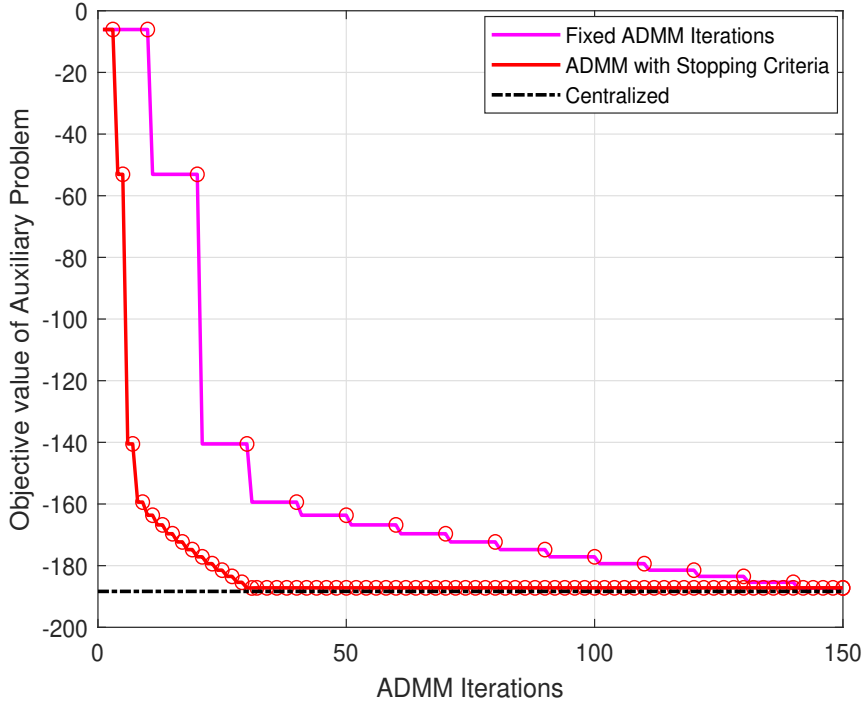


Figure 8. Convergence of the proposed ADMM method with stopping criteria.

Figure 9 plots the WSR of the proposed algorithms (Algorithm 5 and 6) versus number of bi-directional signalling iterations for $SNR = 15\text{dB}$. The interference thresholds are fixed to $\{\theta_{bk}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b} = \{\bar{\theta}_n\}_{n \in \mathcal{B}_{UL}} = N_0^{dB}$. The WSR values are computed after step 4 of Algorithm 5 and Algorithm 6. Results show that the proposed algorithms (Algorithm 5 and 6) converge monotonically. It can also be seen that both the proposed algorithms and the centralized solution converge within 20 bi-directional signalling iterations.

Figure 10 shows the cumulative distribution function (CDF) of the aggregated inter operator interference power at the UL operator BSs and DL operator users for $SNR = 5\text{dB}$. As a reference, we run the Algorithm 6 (OTA-RS:MSE) without the interference constraints (labelled using $\theta_{bk} = \bar{\theta}_n = \infty$ in the plots). The interference thresholds for both UL-to-DL micro-operator and DL-to-UL micro-operator are set to 3dB above the noise level *i.e.*, $\{\theta_{bk} = N_0 + 3\text{dB}\}_{b \in \mathcal{B}_{DL}, k \in \mathcal{K}_b} = \{\bar{\theta}_n = N_0 + 3\text{dB}\}_{n \in \mathcal{B}_{UL}}$. The plot incorporates the inter operator interference power over 500 channel realizations calculated

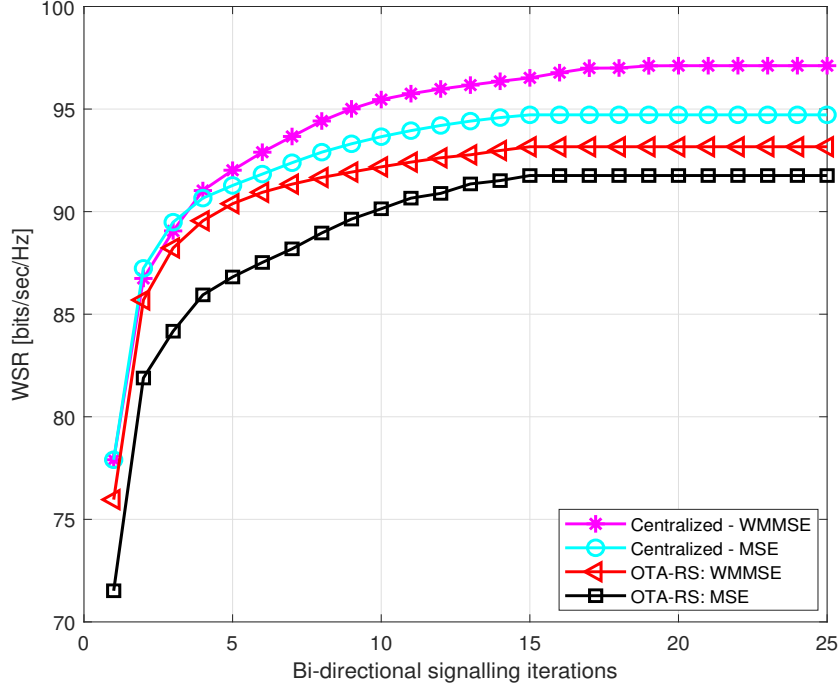


Figure 9. Convergence of the proposed OTA algorithm.

after step 5 of Algorithm 6. Results show that the proposed Algorithm 6 maintains the UL-to-DL interference (solid blue line in the figure) below the threshold θ_{bk} for almost all of the time. On the other hand, when interference constraint is not employed, the UL-to-DL interference (dotted blue line) violates the threshold for more than 95% of time. Similarly, the algorithm manages to limit the DL-to-UL interference (solid magenta line) for about 95% of the time as compared to the case without interference constraints (dotted magenta line) where it violates the threshold $\bar{\theta}_n$ for almost 80% of the time.

Figure 11 shows the CDF of per user rate achieved by Algorithm 5 (OTA-RS:WMMSE) and Algorithm 6 (OTA-RS:MSE) for SNR = 5dB. The interference thresholds for both UL-to-DL micro-operator and DL-to-UL micro-operator are set to 3dB above the noise level *i.e.*, $\{\theta_{bk} = N_0 + 3\text{dB}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b} = \{\bar{\theta}_n = N_0 + 3\text{dB}\}_{n \in \mathcal{B}_{\text{UL}}}$. The results incorporate the user rates achieved by DL and UL μOP over 500 channel realizations. The solid blue and magenta line represent the UL operator user rate and DL operator user rate, respectively, achieved by Algorithm 6. The dotted blue and magenta line represent the UL user rate and DL user rate, respectively, achieved by Algorithm 6. Results show that Algorithm 6 provides better fairness to the user rates as compared to Algorithm 5, where the user rates are more dispersed. This can be linked to the fact that, WMMSE approach does not provide fairness to the users and can allocate more resources to some users and can shut some users with higher interference to achieve maximum sum rate. On the other hand, MSE tries to provide fair resource allocation to all the users.

Figure 12 shows the average WSR versus SNR for the Algorithm 5 (OTA-RS:WMMSE) and Algorithm 6 (OTA-RS:MSE) with and without interference constraints. The interference thresholds for both UL-to-DL micro-operator and DL-to-UL micro-operator are set to 3dB above the noise level *i.e.*, $\{\theta_{bk} = N_0 + 3\text{dB}\}_{b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b} = \{\bar{\theta}_n =$

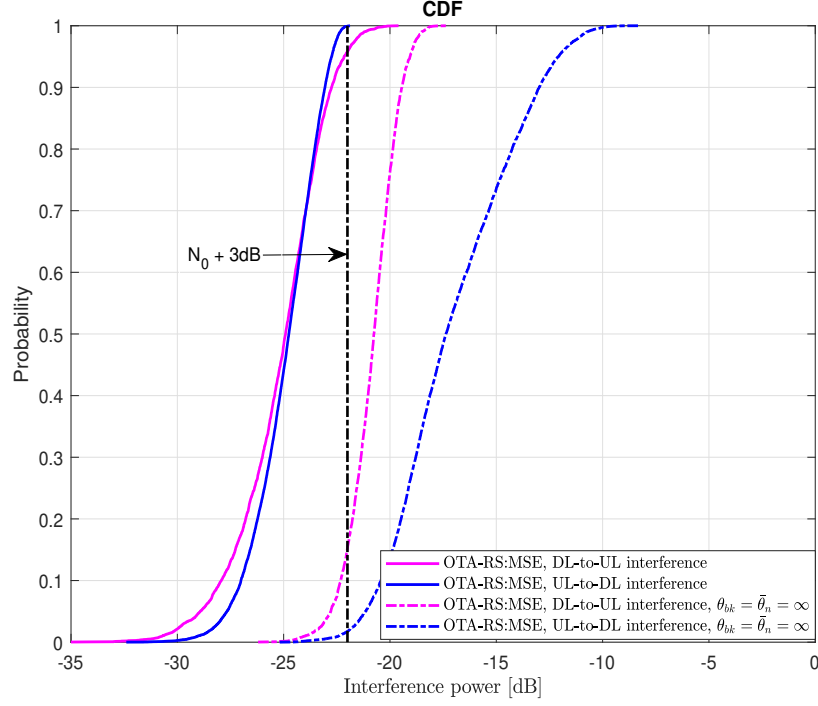


Figure 10. CDF of aggregate interference at the UL operator BS and DL operator user.

$N_0 + 3\text{dB}\}_{n \in \mathcal{B}_{\text{UL}}}$. As a reference, we run both algorithms 5 and 6 without performing RS measurements in step 1 of these algorithms. So, we divide the UL-to-DL threshold θ_{bk} equally among all UL operator users such that $\{\bar{\chi}_{nl,bk} = \theta_{bk} / (\sum_{n \in \mathcal{B}_{\text{UL}}} K_n)\}_{n \in \mathcal{B}_{\text{UL}}, l \in \mathcal{K}_n, b \in \mathcal{B}_{\text{DL}}, k \in \mathcal{K}_b}$ and the aggregated threshold can be maintained. These results we denote by 'OTA:WMMSE' and 'OTA-MSE' in the plot. Each curve in the figure is averaged over 500 channel realizations. It can be seen from the results that WMMSE approach provides better sum rate than the MSE approach. Results also show that Algorithm 6 provides slightly better sum rate when the UL-to-DL interference thresholds are fixed based on RS measurements instead of equal interference budget allocations. This is because, while allocating interference budget via RS measurements, the UL operator allocates interference budget for users based on their channel gains. This in turn benefits both near and far users compared to equal interference budget allocations.

Figure 13 and Figure 14 show the average WSR versus SNR for Algorithm 5 (OTA-RS;WMMSE) and Algorithm 6 (OTA-RS;MSE) with varying interference thresholds. When the interference thresholds are set to higher levels, the transmitters can transmit with more power, increasing the spectral efficiency of the system. But, as interference thresholds are lowered, the interference constraints become tighter, limiting the transmit power for the transmitters. This decreases the spectral efficiency of the system. As the interference thresholds are lowered further, the transmit power is limited by the interference constraints, irrespective of the maximum available transmit power. Thus, there is no decline in achievable sum rates as seen in the results.

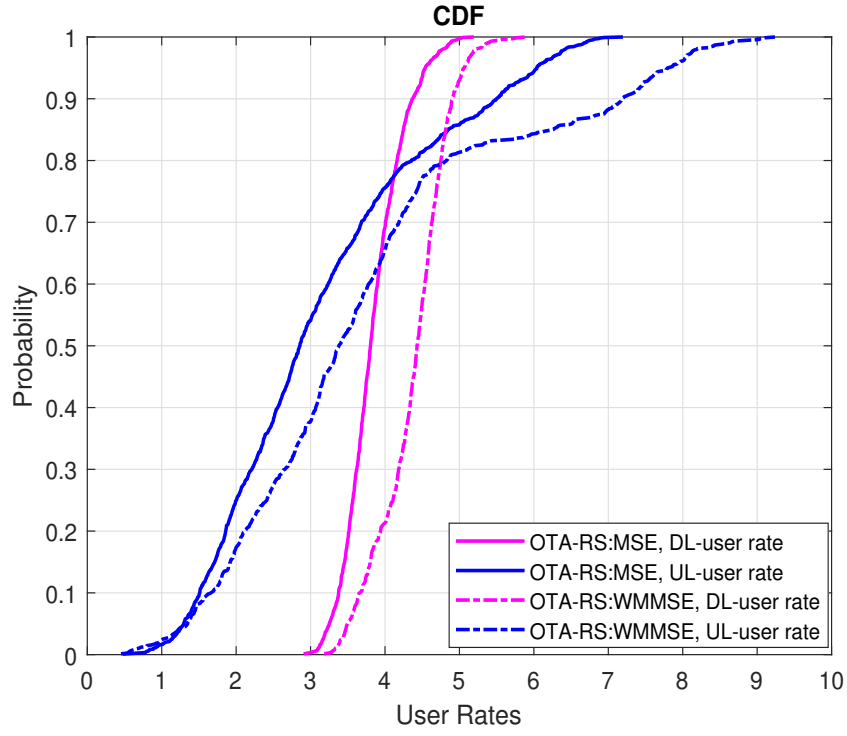


Figure 11. CDF of UL and DL operator user rates.

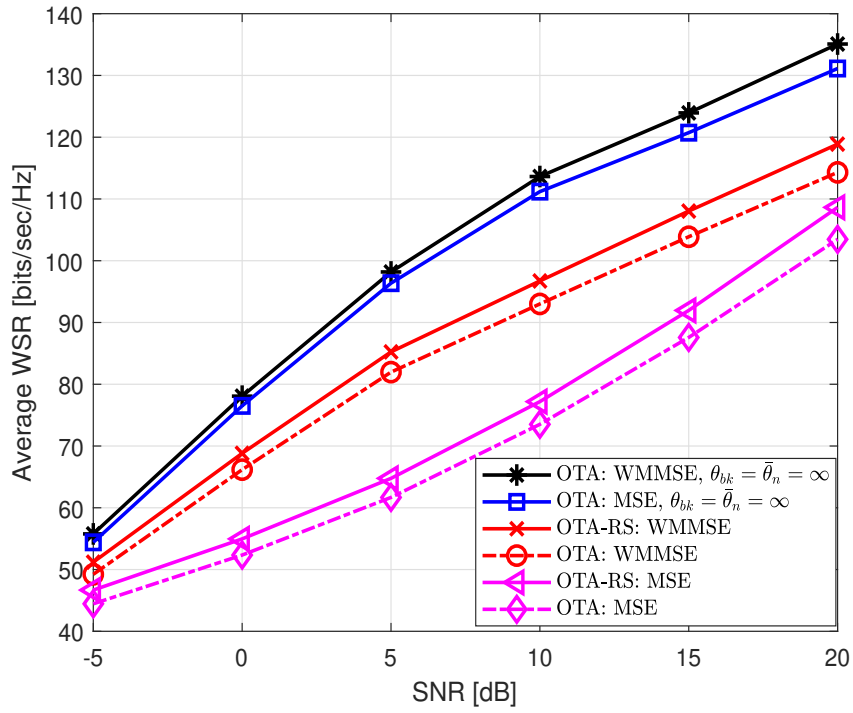


Figure 12. Average sum rate achieved at various SNR.

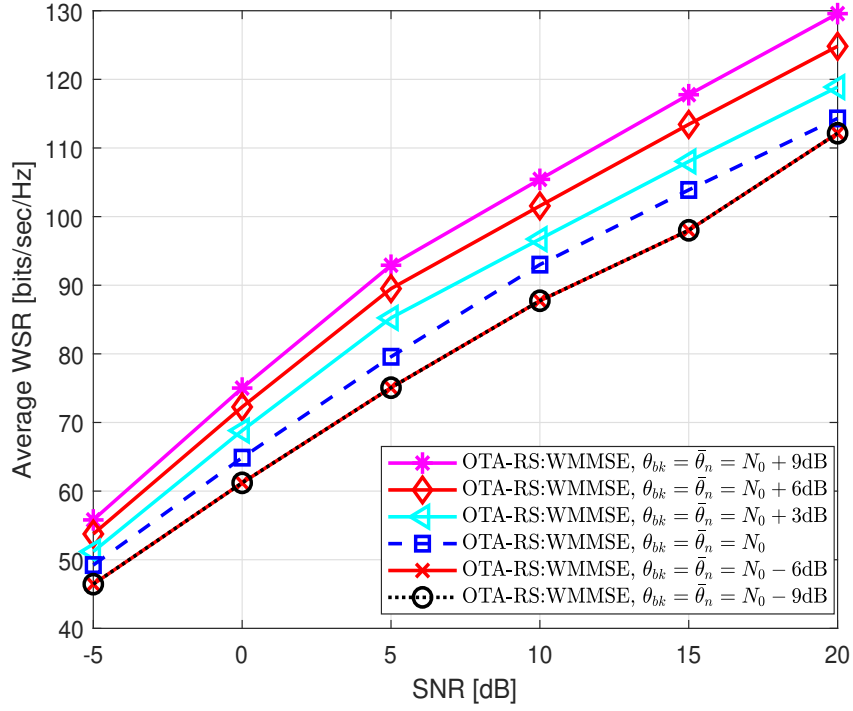


Figure 13. Average sum rate achieved at various SNR with various interference levels by Algorithm 5.

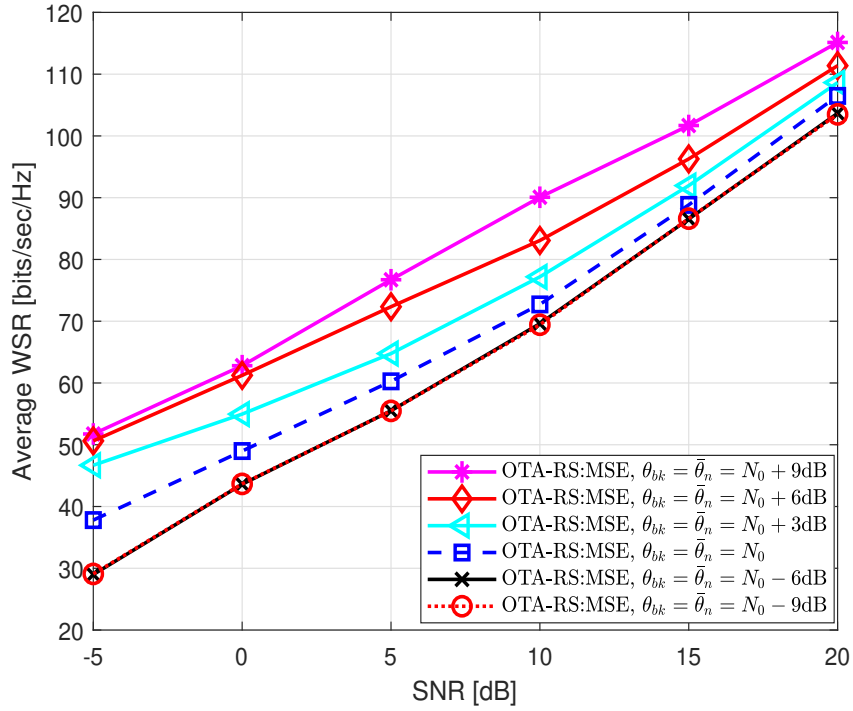


Figure 14. Average sum rate achieved at various SNR with various interference levels by Algorithm 6.

6 DISCUSSION

The aim of this thesis is to maximize the spectral efficiency of a system with two μ OPs in dynamic TDD mode and provide aggregated interference protection between the μ OPs. Several inter-operator spectrum sharing algorithms which manage the inter-operator interference and maximize the spectral efficiency have been studied in literature. But, spectrum sharing algorithms for μ OPs is still a hot topic for research. In this regard, two distributed algorithms based on WMMSE and WSMSE have been proposed. The algorithms maximize the spectral efficiency of the system while guaranteeing that the inter-micro-operator interference remains below a specified threshold.

The multi-user multi-cell MIMO system model and problem formulation for two μ OPs operating in different DL/UL configuration with dynamic TDD is presented with mathematical description in Chapter 3. The problem formulated in Chapter 3 is non-convex, NP-hard and the requirement of centralized CSI makes it even more challenging to solve. Furthermore, the coupled interference constraints add to the difficulty of solving the problem in a distributed manner.

Equivalent reformulation of the WSRM problem into WMMSE minimization and WSMSE minimization is considered in Chapter 4. Alternating optimization technique is applied to make the reformulated jointly non-convex problems a convex problem. To achieve the distributed implementation, consensus-ADMM method is used to decouple the DL optimization problem across each DL-operator BS. To decouple the UL optimization problem across each UL-operator user, an interference budget allocation scheme based on RS measurements has been proposed. The UL optimization problem is a QCQP problem. Hence consensus-ADMM for general QCQP is applied to solve the problem at each UL-operator user. Therefore, the original optimization problem can be solved at each DL-operator BS and UL-operator user using local CSI.

Forward and backward over-the-air pilot training strategy is considered in the proposed algorithms to extract all required parameters to estimate the precoders. The precoders are designed at each DL BS and UL user by exchanging only some coupling variables between the coordinating BSs and users instead of the full CSI exchange. Hence, these distributed algorithms reduce the large control information exchange required in the centralized approach.

The numerical analysis of the proposed algorithms are provided in Chapter 5. The numerical simulations showed that the proposed algorithms can limit the inter-micro-operator interference within the specified threshold for most of the time. In addition to managing the inter-micro-operator interference, the WMMSE approach provides better sum rates than the WSMSE approach. This can be linked to the fact that WMMSE approach does not allocate fair resources to all the users and can allocate more resources to some users and shut some highly interfering users to achieve maximum sum rate. In contrast, the MSE approach tries to allocate fair resources to all the users.

Another important observation from the simulation results is that the greater the interference threshold, the better sum rates can be achieved. It was also noticed that on decreasing the interference threshold, a point is reached where there is no further decline in sum rates. This can be attributed to the fact that on decreasing the interference threshold, the interference constraints become tighter and limit the transmit power despite of the maximum available transmit power. Thus, receivers need to be designed in such a way that they can handle higher interference from other transmitters.

A heuristic approach to allocate interference budgets to the users in UL micro-operator has been considered in this work. Hence, as a future work, a more practical interference budget allocation scheme for UL micro-operator users can be a good research problem. We can also consider extending this work with hybrid beamforming, since digital beamforming is not necessarily practically suitable for systems with large antenna array. As a final extension, we can also consider pilot allocation algorithm for mitigating pilot contamination when non-orthogonal pilots are used.

7 SUMMARY

The main focus of this thesis work was to maximize the spectral efficiency of a system with two μ OPs operating in dynamic TDD mode and provide guaranteed inter-micro-operator interference protection. The prime goal was to limit the coordination between the micro operators and design precoders to guarantee interference protection between the micro-operators. In this regard, a single-stage system utility maximization problem in the form of WSRM was formulated. Since, WSRM problem is non-convex and NP-hard, we proposed two different equivalent reformulation of the WSRM problem.

At first, the decentralized precoder design by transforming the WSRM problem into an equivalent WMMSEMin problem was discussed. Here, the precoders are designed at each DL-operator BS and UL-operator UE with local CSI by exchanging coupling variables among the coordinating BSs and UEs. In the proposed algorithm, OTA bi-directional signalling with RS measurements is used to exchange the interference to update the precoders. To decentralize the precoder design, we employ ADMM technique by relaxing the inter-micro-operator interference as an optimization variable by including it in each DL-operator BS objective and UL-operator UE objective. The exchange of coupling variables at the DL-operator takes place via backhaul and the exchange of coupling variables at UL-operator takes place via backhaul and feedback link between UE and BS. The WMMSEMin approach does not provide fairness to all the users. Thus, an alternative decentralized precoder design algorithm based on WSMSE reformulation of the WSRM problem was proposed to provide inherent fairness to all the users.

The performances of both the proposed algorithms were analyzed based on numerical simulations. The simulation results show that both the proposed algorithms provide the required inter-micro-operator interference protection maintaining acceptable sum rates compared to the benchmark. The results also prove that the WMMSEMin approach is not fair to all the users as compared to the WSMSE approach.

8 REFERENCES

- [1] Series M. (2015) IMT vision–framework and overall objectives of the future development of IMT for 2020 and beyond. Recommendation ITU 2083.
- [2] Nakamura T., Nagata S., Benjebbour A., Kishiyama Y., Hai T., Xiaodong S., Ning Y. & Nan L. (2013) Trends in small cell enhancements in LTE advanced. *IEEE Communications Magazine* 51, pp. 98–105.
- [3] Matinmikko M., Latva-Aho M., Ahokangas P., Yrjölä S. & Koivumäki T. (2017) Micro operators to boost local service delivery in 5G. *Wireless Personal Communications* 95, pp. 69–82.
- [4] Wenjia Liu, Shengqian Han, Chenyang Yang & Chengjun Sun (2013) Massive MIMO or small cell network: Who is more energy efficient? In: 2013 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), pp. 24–29.
- [5] Liu C. & Wang L. (2016) Optimal cell load and throughput in green small cell networks with generalized cell association. *IEEE Journal on Selected Areas in Communications* 34, pp. 1058–1072.
- [6] Apostolidis A., Campoy L., Chatzikokolakis K., Friederichs K., Irnich T., Koufos K., Kronander J., Luo J., Mohyeldin E., Olmos P. et al. (2013) Intermediate description of the spectrum needs and usage principles. METIS Deliverable D 5, p. 1.
- [7] Jorswieck E.A., Badia L., Fahldieck T., Karipidis E. & Luo J. (2014) Spectrum sharing improves the network efficiency for cellular operators. *IEEE Communications Magazine* 52, pp. 129–136.
- [8] Spyropoulos I. & Zeidler J.R. (2009) Supporting asymmetric traffic in a TDD/CDMA cellular network via interference-aware dynamic channel allocation and space–time LMMSE joint detection. *IEEE Transactions on Vehicular Technology* 58, pp. 744–759.
- [9] Chan P.W., Lo E.S., Wang R.R., Au E.K., Lau V.K., Cheng R.S., Mow W.H., Murch R.D. & Letaief K.B. (2006) The evolution path of 4G networks: FDD or TDD? *IEEE Communications Magazine* 44, pp. 42–50.
- [10] Omiyi P., Haas H. & Auer G. (2007) Analysis of TDD cellular interference mitigation using busy-bursts. *IEEE Transactions on Wireless Communications* 6, pp. 2721–2731.
- [11] Hiltunen K., Matinmikko-Blue M. & Latva-Aho M. (2018) Impact of interference between neighbouring 5G micro operators. *Wireless Personal Communications* 100, pp. 127–144.
- [12] Pennanen H., Tölli A. & Latva-aho M. (2014) Multi-cell beamforming with decentralized coordination in cognitive and cellular networks. *IEEE Transactions on Signal Processing* 62, pp. 295–308.

- [13] Komulainen P., Tölli A. & Juntti M. (2013) Effective CSI signaling and decentralized beam coordination in TDD multi-cell MIMO systems. *IEEE Transactions on Signal Processing* 61, pp. 2204–2218.
- [14] Björnson E. (2011) Multiantenna Cellular Communications : Channel Estimation, Feedback, and Resource Allocation. Ph.D. thesis, KTHKTH, Signal Processing, ACCESS Linnaeus Centre.
- [15] Kuhn V. (2006) Wireless communications over MIMO channels: applications to CDMA and multiple antenna systems. John Wiley & Sons.
- [16] Tse D. & Viswanath P. (2005) Fundamentals of wireless communication. Cambridge university press.
- [17] Lizhong Zheng & Tse D.N.C. (2003) Diversity and multiplexing: a fundamental tradeoff in multiple-antenna channels. *IEEE Transactions on Information Theory* 49, pp. 1073–1096.
- [18] Telatar E. (1999) Capacity of multi-antenna gaussian channels. *European transactions on telecommunications* 10, pp. 585–595.
- [19] Gesbert D., Kountouris M., Heath R., Chae C. & Salzer T. (2008) From single user to multiuser communications: shifting the MIMO paradigm. *IEEE Signal Processing Magazine* .
- [20] Costa M. (1983) Writing on dirty paper (corresp.). *IEEE transactions on information theory* 29, pp. 439–441.
- [21] Yoo T. & Goldsmith A. (2006) On the optimality of multiantenna broadcast scheduling using zero-forcing beamforming. *IEEE Journal on selected areas in communications* 24, pp. 528–541.
- [22] Lee H., Sohn I., Kim D. & Lee K.B. (2011) Generalized MMSE beamforming for downlink MIMO systems. In: 2011 IEEE International Conference on Communications (ICC), IEEE, pp. 1–6.
- [23] Dai B., Xu W. & Zhao C. (2011) Optimal MMSE beamforming for multiuser downlink with delayed CSI feedback using codebooks. In: 2011 IEEE Global Telecommunications Conference-GLOBECOM 2011, IEEE, pp. 1–5.
- [24] Dabbagh A.D. & Love D.J. (2008) Multiple antenna MMSE based downlink precoding with quantized feedback or channel mismatch. *IEEE Transactions on communications* 56, pp. 1859–1868.
- [25] Choi Y.S., Sohn I. & Lee K.B. (2006) A novel decentralized time slot allocation algorithm in dynamic TDD system. In: CCNC 2006. 2006 3rd IEEE Consumer Communications and Networking Conference, 2006., vol. 2, Citeseer, vol. 2, pp. 1268–1272.
- [26] Chung H.J., Kim M.R., Kim N.M. & Yun S. (2006) Time slot allocation based on region and time partitioning for dynamic TDD-OFDM systems. In: 2006 IEEE 63rd Vehicular Technology Conference, vol. 5, IEEE, vol. 5, pp. 2459–2463.

- [27] Spencer Q.H. & Haardt M. (2002) Capacity and downlink transmission algorithms for a multi-user MIMO channel. In: Conference Record of the Thirty-Sixth Asilomar Conference on Signals, Systems and Computers, 2002., vol. 2, IEEE, vol. 2, pp. 1384–1388.
- [28] Li W. & Latva-aho M. (2010) An efficient channel block diagonalization method for generalized zero forcing assisted MIMO broadcasting systems. *IEEE transactions on wireless communications* 10, pp. 739–744.
- [29] Tervo O., Pennanen H., Christopoulos D., Chatzinotas S. & Ottersten B. (2017) Distributed optimization for coordinated beamforming in multicell multigroup multicast systems: Power minimization and SINR balancing. *IEEE Transactions on Signal Processing* 66, pp. 171–185.
- [30] Jayasinghe P., Tölli A., Kaleva J. & Latva-aho M. (2018) Bi-directional beamformer training for dynamic TDD networks. *IEEE Transactions on Signal Processing* 66, pp. 6252–6267.
- [31] Kaleva J., Tölli A. & Juntti M. (2016) Decentralized sum rate maximization with QoS constraints for interfering broadcast channel via successive convex approximation. *IEEE Transactions on Signal Processing* 64, pp. 2788–2802.
- [32] Aquilina P., Cirik A.C. & Ratnarajah T. (2017) Weighted sum rate maximization in full-duplex multi-user multi-cell MIMO networks. *IEEE Transactions on Communications* 65, pp. 1590–1608.
- [33] Shi S., Schubert M. & Boche H. (2008) Rate optimization for multiuser MIMO systems with linear processing. *IEEE Transactions on Signal Processing* 56, pp. 4020–4030.
- [34] Christensen S.S., Agarwal R., De Carvalho E. & Cioffi J.M. (2008) Weighted sum-rate maximization using weighted MMSE for MIMO-BC beamforming design. *IEEE Transactions on Wireless Communications* 7, pp. 4792–4799.
- [35] Weeraddana P.C., Codreanu M., Latva-aho M. & Ephremides A. (2012) Multicell MISO downlink weighted sum-rate maximization: A distributed approach. *IEEE transactions on signal processing* 61, pp. 556–570.
- [36] Tölli A., Pennanen H. & Komulainen P. (2010) Decentralized minimum power multi-cell beamforming with limited backhaul signaling. *IEEE Transactions on Wireless Communications* 10, pp. 570–580.
- [37] Pennanen H., Tölli A. & Latva-aho M. (2011) Decentralized coordinated downlink beamforming for cognitive radio networks. In: 2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications, pp. 566–571.
- [38] Shen C., Chang T.H., Wang K.Y., Qiu Z. & Chi C.Y. (2012) Distributed robust multicell coordinated beamforming with imperfect CSI: An ADMM approach. *IEEE Transactions on signal processing* 60, pp. 2988–3003.

- [39] ETSI (2001) Transmission and Multiplexing (TM); Time Division Duplex (TDD) in Point-to-Multipoint (P-MP) Fixed Wireless Access (FWA) systems; Characteristics and network applications. Technical Report (TR) 101 904, European Telecommunications Standards Institute (ETSI). Version 1.1.1.
- [40] Esmailzadeh R., Nakagawa M. & Sourour E.A. (1997) Time-division duplex CDMA communications. *IEEE Personal Communications* 4, pp. 51–56.
- [41] Celik H. & Sung K.W. (2015) On the feasibility of blind dynamic TDD in ultra-dense wireless networks. In: 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), pp. 1–5.
- [42] Celik H. (2017), On the performance of dynamic TDD in ultra-dense wireless access networks. QC 20170922.
- [43] Ding M., Pérez D.L., Vasilakos A.V. & Chen W. (2014) Dynamic TDD transmissions in homogeneous small cell networks. In: 2014 IEEE International Conference on Communications Workshops (ICC), IEEE, pp. 616–621.
- [44] Jeong W. & Kavehrad M. (2002) Cochannel interference reduction in dynamic-TDD fixed wireless applications, using time slot allocation algorithms. *IEEE Transactions on Communications* 50, pp. 1627–1636.
- [45] Yun J. & Kavehrad M. (2004) Adaptive resource allocations for D-TDD systems in wireless cellular networks. In: IEEE MILCOM 2004. Military Communications Conference, 2004., vol. 2, IEEE, vol. 2, pp. 1047–1053.
- [46] Shi C., Berry R.A. & Honig M.L. (2013) Bi-directional training for adaptive beamforming and power control in interference networks. *IEEE transactions on signal processing* 62, pp. 607–618.
- [47] Jayasinghe P., Tölö A., Kaleva J. & Latva-aho M. (2015) Bi-directional signaling for dynamic TDD with decentralized beamforming. In: 2015 IEEE International Conference on Communication Workshop (ICCW), pp. 185–190.
- [48] Jayasinghe P., Tölö A., Kaleva J. & Latva-aho M. (2018) Bi-directional beamformer training for dynamic TDD networks. *IEEE Transactions on Signal Processing* 66, pp. 6252–6267.
- [49] Tölö A., Kaleva J., Venkatraman G. & Gesbert D. (2016) Joint UL/DL mode selection and transceiver design for dynamic TDD systems. In: 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), pp. 630–634.
- [50] Jayasinghe P., Tölö A., Kaleva J. & Latva-Aho M. (2017) Direct beamformer estimation for dynamic TDD networks with forward-backward training. In: 2017 IEEE 18th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), IEEE, pp. 1–6.
- [51] Parkvall S., Dahlman E., Furuskar A. & Frenne M. (2017) Nr: The new 5G radio access technology. *IEEE Communications Standards Magazine* 1, pp. 24–30.

- [52] 3GPP (2018) Technical specification group radio access network; Physical channels and modulation (Release 15). Technical Specification (TS) 38.211, 3rd Generation Partnership Project (3GPP). Version 15.2.0.
- [53] Palomar D.P. (2003) A unified framework for communications through MIMO channels. Ph. D. dissertation, Technical Univ. Catalonia (UPC) .
- [54] Boyd S. & Vandenberghe L. (2004) Convex optimization. Cambridge university press.
- [55] Boyd S., Parikh N., Chu E., Peleato B. & Eckstein J. (2011) Distributed optimization and statistical learning via the alternating direction method of multipliers. *Foundations and Trends® in Machine learning* 3, pp. 1–122.
- [56] Luo Z.Q., Ma W.K., So A.M.C., Ye Y. & Zhang S. (2010) Semidefinite relaxation of quadratic optimization problems. *IEEE Signal Processing Magazine* 27, pp. 20–34.
- [57] Huang K. & Sidiropoulos N.D. (2016) Consensus-ADMM for general quadratically constrained quadratic programming. *IEEE Transactions on Signal Processing* 64, pp. 5297–5310.
- [58] Manosha K.B.S., Codreanu M., Rajatheva N. & Latva-aho M. (2014) Power-throughput tradeoff in MIMO heterogeneous networks. *IEEE Transactions on Wireless Communications* 13, pp. 4309–4322.
- [59] Shi Q., Razaviyayn M., Luo Z. & He C. (2011) An iteratively weighted MMSE approach to distributed sum-utility maximization for a MIMO interfering broadcast channel. *IEEE Transactions on Signal Processing* 59, pp. 4331–4340.
- [60] Komulainen P., Tölli A. & Juntti M. (2013) Effective CSI signaling and decentralized beam coordination in TDD multi-cell MIMO systems. *IEEE Transactions on Signal Processing* 61, pp. 2204–2218.
- [61] Jayasinghe P., Tölli A. & Latva-aho M. (2015) Bi-directional signaling strategies for dynamic TDD networks. In: 2015 IEEE 16th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), pp. 540–544.